House of Finance

Working Paper Series

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How do banks react to catastrophic events? Evidence from Hurricane Katrina

SAFE Working Paper No. 94

SAFE | Sustainable Architecture for Finance in Europe
A cooperation of the Center for Financial Studies and Goethe University Frankfurt

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Non-Technical Summary

An important question is how banks navigate through economic crises because bank financing is crucial for economic recovery and development. From a policy perspective it would be desirable that banks continue to provide financing to borrowers, but that they also maintain their stability in an unfavorable market environment that is adversely affecting their asset quality. Related studies analyse bank lending in the wake of a crisis, but little is known how banks' business decisions affect bank stability during such times, how this is related to their asset allocations, and how the structure of the local banking system is related to economic development in affected areas after a crisis.

This paper first explores how banks adjust their risk-based capital ratios, which are a key determinant of bank stability and a cornerstone of banking regulation. Second, we analyse the mechanisms of these adjustments, i.e., banks' asset allocations and lending. The analysis specifically considers the role of different types of banks with regards to bank structure (independent or part of a bank holding company) and bank capitalization (relatively low or high capital ratios). Finally, we analyse whether characteristics of the local banking system (the share of banks belonging to a bank holding company and the average of banks' risk-based capital ratios by county) are related to local economic developments after a crisis.

The key findings of our empirical analysis are as follows: Independent banks in the disaster areas increase their risk-based capital ratios after the hurricane relative to the control group (unaffected by the shock), while those that are part of a bank holding company on average do not. Independent banks thereby strengthen their buffer against future income shocks and mitigate bankruptcy risks. When we examine low-capitalized and high-capitalized independent banks separately, we find that this precautionary behavior only holds for high-capitalized independent banks. Our analysis also shows that high-capitalized independent banks achieve higher risk-based capital ratios by prioritizing on assets with lower risk weights: They increase their holdings in government securities and reduce their existing loan exposures to non-financial firms relative to the control group. Notably, we also explore banks' new lending transactions with non-financial firms based on a sample from the Small Business Administration loan program, and we find that high-capitalized independent banks also increase their new lending to non-financial firms in their core markets (where they have a branch presence). This suggests that these banks reduce their loan exposures not through reduced new lending, but through other strategies such as loan sales.

Finally, our analysis provides new evidence on the role of the structure of the banking system to foster growth and employment in the post-Katrina period. We assess whether affected counties that host a relative small or large number of independent banks (not part of a bank holding company) and banks with relatively low or high pre-Katrina capital ratios develop differently in the post crisis period. Our evidence shows that a higher share of independent banks as well as relatively high average capital ratios of counties are associated with better economic growth of total personal income and employment relative to other counties (with less independent banks or lower average bank capital ratios). This has important policy implications because it suggests that the promotion of independent (locally focused) banks as well as higher bank capital requirements may mitigate economic costs in areas affected by a crisis. In particular, we find that the change (before versus after the natural disaster) in total personal income and employment of an affected county is about 5 percentage points and 4 percentage points higher, respectively, if the county has a relatively large share of independent and high-capitalized bank versus a county with only BHC banks and relatively low-capitalized banks.

How do banks react to catastrophic events? Evidence from Hurricane Katrina*

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This version: September 2017

Abstract

This paper explores how banks react to an exogenous shock caused by Hurricane Katrina in 2005, and how the structure of the banking system affects economic development following the shock. Independent banks based in the disaster areas increase their risk-based capital ratios after the hurricane, while those that are part of a bank holding company on average do not. The effect on independent banks mainly comes from the subgroup of high-capitalized banks. These independent and high-capitalized banks increase their holdings in government securities and reduce their total loan exposures to non-financial firms, while they also increase new lending to these firms. Regarding local economic developments, affected counties with a relatively large share of independent and high-capitalized banks exhibit higher economic growth than the other affected counties after the catastrophic event.

Keywords: catastrophic events, bank regulation, capital ratios, banking structure, economic development

JEL Classification: G21, G28

*We thank Marcel Blum, Franziska Bremus, Martin Brown, Don Chance, Horst Entorf, Igor Goncharov, Florian Heider, Jan P. Krahnen, Gregory Nini, Jörg Rocholl, Joao Santos, Alexander Schäfer, Reinhard H. Schmidt, Isabel Schnabel, Adi Sunderam, Marcel Tyrell, Greg Udell, Laurent Weill, participants at the 2012 AEA annual meeting in Chicago, the 2012 CEPR Winter Conference on Financial Intermediation in Lenzerheide, the 2012 Financial Intermediation Research Society conference in Minneapolis, the 2012 European Finance Association annual meeting in Copenhagen, the 2012 DGF annual meeting in Hannover, the 2012 GEABA symposium in Graz, the 2012 Verein für Socialpolitik annual meeting in Göttingen, the 2012 French Finance Association (AFFI) annual meeting in Strasbourg as well as seminar participants at the Bank of England, Banque de France, Bank of Hungary, Bundesbank, German Institute for Economic Research (DIW Berlin), Sveriges Riksbank and UZH Zurich in 2013 for valuable comments and suggestions. Ulrich Schüwer gratefully acknowledges financial support from the Research Center SAFE, funded by the State of Hessen research initiative LOEWE. The paper represents the authors' personal opinions and does not necessarily reflect the views of the institutions with which they are affiliated.

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1 Introduction

An important question is how banks navigate through economic crises because bank financing is crucial for economic recovery and development. From a policy perspective it would be desirable that banks continue to provide financing to borrowers, but that they also maintain their stability in an unfavorable market environment that is adversely affecting their asset quality. Related studies analyse bank lending in the wake of a crisis (e.g., Gan, 2007; Garmaise and Moskowitz, 2009; Ivashina and Scharfstein, 2010; Puri et al., 2011; De Haas and Van Horen, 2013; Cortes and Strahan, 2017),[1] but little is known how banks' business decisions affect bank stability during such times, how this is related to their asset allocations, and how the structure of the local banking system is related to economic development in affected areas after a crisis.[2]

This paper first explores how banks adjust their risk-based capital ratios, which are a key determinant of bank stability and a cornerstone of banking regulation. Second, we analyse the mechanisms of these adjustments, i.e., banks' asset allocations and lending. The analysis specifically considers the role of different types of banks with regards to bank structure (independent or part of a bank holding company) and bank capitalization (relatively low or high capital ratios). Finally, we analyse whether characteristics of the local banking system (the share of banks belonging to a bank holding company and the average of banks' risk-based capital ratios by county) are related to local economic developments after a crisis.

It is not clear what findings to expect from these analyses, because different arguments point in different directions. In particular, banks may increase their capital ratios to foster financial stability and protect their franchise values, or they may decrease capital

[1]The different crises explored in these studies are the land market collapse in Japan in the early 1990s (Gan, 2007), natural disasters (Garmaise and Moskowitz, 2009; Cortes and Strahan, 2017) and the recent financial crisis (all others).

[2]An exemption regarding the latter aspect is Cortes (2014) who shows that the presence of local lenders is beneficial for job creation after natural disasters.

ratios to profit from risk-shifting in times of crisis. These strategies may be associated with decreased or increased lending, respectively. Finally, the presence of a relatively large share of independent banks may be associated with relatively high economic growth, because these banks are typically locally focused and may have advantages in screening and monitoring local borrowers, or it may be associated with relatively low economic growth, because these banks are typically less diversified and more capital constrained relative to banks belonging to bank holding companies.

The challenge for the analysis is twofold: First, to identify the direction of the relationship between a crisis and the banks' business decisions.[3] Second, to control for parallel economic developments, which may also affect banks' financial figures but not result from active changes in banks' financing or investment decisions. In order to identify causality between a crisis and banks' business decisions we use Hurricane Katrina and two contemporary hurricanes, which struck the U.S. Gulf Coast in the third and fourth quarters of 2005, as a natural experiment. Hurricane Katrina ranks among the costliest natural disasters in United States history with estimated property damages ranging from $100 to over $200 billion (National Hurricane Center, 2005; Congleton, 2006). The hurricanes exposed banks in the U.S. Gulf Coast region to unexpected losses and weakened their asset quality because a large part of the damages for borrowers was not insured. Further, it caused uncertainty for banks with respect to how individual and commercial borrowers would cope with the damages. Asymmetric information between banks and their borrowers increased and it was also uncertain how the overall economy in the affected regions would recover from the shock. The FDIC (2006) characterized the situation as follows:

> *Hurricane Katrina had a devastating effect on the U.S. Gulf Coast region that will continue to affect the business activities of the financial institutions serving this area for the foreseeable future. Some of these institutions may face signifi-*

[3] The direction of the relationship is difficult to identify because, on the one hand, a crisis affects banks' business decisions, and on the other hand, banks' business decisions may cause a crisis if many banks make similar financing or investment decisions.

cant loan quality issues caused by business failures, interruptions of borrowers' income streams, increases in borrowers' operating costs, the loss of jobs, and uninsured or underinsured collateral damage.

Along the same lines, the major rating agencies announced close monitoring of capital adequacy and the risk-management processes of affected banks in the aftermath of Hurricane Katrina (Moody's, 2005a,b). Hurricane Katrina also led to a change in the perceived hurricane risks, as reflected in property insurance premium increases of 30% or more (USA TODAY, 2010).

Using this natural experiment we analyse a large sample of U.S. banks within a difference-in-difference framework. The treatment group comprises affected banks while the control group comprises unaffected banks in the U.S. Gulf Coast region and neighboring states. When the analysis turns to local economic developments after the 2005 hurricane season we use a corresponding sample of affected and unaffected counties.

The key findings of our empirical analysis are as follows: Independent banks in the disaster areas increase their risk-based capital ratios after the hurricane relative to the control group (unaffected by the shock), as illustrated in Panel (a) of Figure 1, while those that are part of a bank holding company on average do not. Independent banks thereby strengthen their buffer against future income shocks and mitigate bankruptcy risks. Our results hence suggest that asset quality is an important determinant of banks' risk-based capital ratios as long as a bank is not backed by a larger banking organization. When we examine low-capitalized and high-capitalized independent banks separately, we find that this precautionary behavior only holds for high-capitalized independent banks. A potential explanation is that banks with high franchise values and/or high bankruptcy costs have incentives to avoid bankruptcy, and are thus characterized by high-capital ratios (before a hurricane) and precautionary behavior (after a hurricane). Our analysis also shows that high-capitalized independent banks achieve higher risk-based capital ratios by prioritizing on assets with lower risk weights: They increase their holdings in government securities and reduce their existing loan exposures to non-financial firms relative to the control group. The latter is illustrated in Panel (b) of Figure 1, where banks' loan exposures to non-financial firms are represented by the ratio of the volume of commercial and industrial loans (C&I loans) to assets. Notably, we also explore banks' *new* lending transactions with non-financial firms based on a sample from the *Small Business Administration* loan program, and we find that high-capitalized independent banks also increase their new lending to non-financial firms in their core markets (where they have a branch presence). This suggests that these banks reduce their loan exposures not through reduced new lending, but through other strategies such as loan sales.

Finally, our analysis provides new evidence on the role of the structure of the banking system to foster growth and employment in the post-Katrina period. We assess whether affected counties that host a relative small or large number of independent banks (not part of a bank holding company) and banks with relatively low or high pre-Katrina capital ratios develop differently in the post crisis period. Our evidence shows that a higher share of independent banks as well as relatively high average capital ratios of counties are associated with better economic growth of total personal income and employment relative to other counties (with less independent banks or lower average bank capital ratios). This has important policy implications because it suggests that the promotion of independent (locally focused) banks as well as higher bank capital requirements may mitigate economic costs in areas affected by a crisis. In particular, we find that the change (before versus after the natural disaster) in total personal income and employment of an affected county is about 5 percentage points and 4 percentage points higher, respectively, if the county has a relatively large share of independent and high-capitalized bank versus a county with only BHC banks and relatively low-capitalized banks.[4]

[4]These numbers seem to be very high, but a recent study by Jordà et al. (2017) also finds very high effects for a cross-country sample with data from 1870 to 2013. In particular, they find that "over the 5-year period after the peak of economic activity, the cumulative GDP costs of a financial crisis hitting a below-average capitalized banking sector amount, on average, to more than 13 percentage points lower GDP per capita compared to a financial crisis hitting an above-average capitalized banking sector."

[Figure 1]

Our research contributes to several strands of literature. First, we contribute to the literature that analyses the relationship between asset quality (or, related, asset risk) and bank capital, using a natural experiment as identification strategy. Previous studies face the difficulty that asset quality and bank capital are typically determined simultaneously by banks. Using simultaneous equations, two-stage, or standard OLS estimation techniques, these studies typically find a positive relation between asset risk and capital ratios, i.e., a negative relation between asset quality and capital ratios (e.g., Shrieves and Dahl, 1992; Flannery and Rangan, 2008; Gropp and Heider, 2010). Our findings are in line with findings from these studies and add further evidence on the relation between a bank's asset quality and risk-based capital ratios, using an exogenous shock on banks' asset quality. Importantly, we also consider different bank characteristics, i.e., independent banks versus banks that are part of a bank holding company and low-capitalized versus high-capitalized banks, providing evidence of how these characteristics are related to the banks' risk-based capital ratio adjustments in the wake of a crisis. Previous empirical evidence on the role of risk-based capital ratios shows a positive relation between this measure and bank stability. E.g., Berger and Bouwman (2013) find that higher pre-crisis bank capital, measured as equity-to-assets or risk-based capital ratio, is associated with higher survival probability during a banking crisis. Demirguc-Kunt et al. (2013) show that higher leverage and regulatory capital ratios are associated with better stock market performance during the financial crisis. Hence, our results on banks' capital ratio adjustments are also relevant for the understanding of bank stability.

Further, the results of this paper contribute to studies that evaluate the consequences of various types of crisis on bank lending. For example, using the land-price collapse in Japan in the early 1990s as exogenous shock, Gan (2007) reports that firms with greater collateral losses receive less credit and reduce investments. Garmaise and Moskowitz (2009) use the 1994 Northridge earthquake in California to show that earthquake risk impacts credit markets through a more than 20 percent decreased provision of commercial real estate loans. Chavaz (2016) finds that banks with more concentrated portfolios in markets affected by the 2005 hurricanes maintain lending in markets hit by the shock and circumvent potential capital constraints through loan sales. Cortes and Strahan (2017) show that following natural disasters, multi-market banks reallocate funds toward markets affected by the disasters (with high credit demand) and away from other markets unaffected by the disasters where they own no branches. Notably, they also find that banks do not reduce lending in unaffected core markets where they own branches. As regards the recent financial crisis, the literature finds that financially stricken banks reduced lending, which also led to lower corporate investment. Ivashina and Scharfstein (2010) find that banks are less likely to cut down on lending if sufficient refinancing from deposits is available such that they do not need to rely on short-term debt. Santos (2011) shows that banks with larger losses during the subprime crisis requested higher loan spreads from their corporate borrowers relative to banks with smaller losses. Puri et al. (2011) find that the U.S. financial crisis led to a contraction in banks' retail lending in Germany for banks that experienced losses within their banking organizations. Further, cross-border lending decreased during the financial crisis (Giannetti and Laeven, 2012), but deeper financial integration of banks in foreign countries is associated with more stable cross-border credit (De Haas and Van Horen, 2013). A study by Berger et al. (2017) finds that, in particular when economic conditions are adverse, small banks have comparative advantages over large banks in alleviating financial constraints of small businesses. Our paper presents complementary evidence that in particular independent banks (not part of a bank holding company) with relatively high pre-Katrina capital ratios reduce their total loan exposures to non-financial firms after the shock caused by Hurricane Katrina, while they also increase new lending to non-financial firms under the Small Business Administration loan program.

Finally, our paper is related to the literature that analyses the role of banks in economic recovery and development following a crisis. Cortes (2014) analyses county level data and shows that the presence of local lenders is beneficial for job creation after natural disasters.

Several cross-country studies suggest that higher average bank capital ratios contribute to quicker recoveries from financial crisis recessions (e.g., Cecchetti et al., 2011; Jordà et al., 2017). Our study contributes to these findings by showing that affected counties with a relatively large share of (local) independent and high-capitalized banks exhibit higher economic growth than the other affected counties after the catastrophic event.

The paper proceeds as follows. In Section 2 we provide background information on the 2005 hurricane season and how it affected the economy in the U.S. Gulf Coast region. Section 3 presents the data and identification strategy. Section 4 shows our empirical model and the estimation results. Section 5 concludes.

2 Background on Hurricane Katrina and the 2005 hurricane season

The heavy winds, rain and flooding brought by Hurricane Katrina met the mainland on August 29, 2005, having swept north from the Gulf of Mexico. Only weeks later, on September 24, 2005, Hurricane Rita came ashore, amplifying the effects of Hurricane Katrina. Finally, one month later in October 2005, Hurricane Wilma made landfall in Florida. Overall the 2005 hurricane season caused massive destruction and had significant negative effects on the economy in the affected U.S. Gulf Coast region.

2.1 Damage estimates

Hurricane Katrina, Rita and Wilma rank among the costliest natural disasters in the history of the United States. Estimated property damages from Hurricane Katrina alone range from approximately $100 billion (National Hurricane Center, 2005; Hazards & Vulnerability Research Institute, 2014), $125 billion to $150 billion (Congressional Research

Service, 2013), and up to over $200 billion (Congleton, 2006). Among its destructive effects, Hurricane Katrina made approximately 300,000 homes uninhabitable, which caused more than 400,000 citizens to move (Congressional Research Service, 2013). While Hurricane Katrina brought significantly more destruction than Hurricane Rita or Hurricane Wilma, all three hurricanes rank among the most intense and costliest hurricanes over the last 100 years (National Hurricane Center, 2011; Hurricane Research Division, 2015).

Estimated yearly losses from natural disasters over the period 1960 to 2012, based on data from the Hazards & Vulnerability Research Institute (2014), are illustrated in Figure 2. The estimate for 2005 is about $120 billion, which includes losses from Hurricane Katrina (about $100 billion), Hurricane Rita (about $10 billion) and Hurricane Wilma (about $10 billion). The figure shows that the losses from the 2005 hurricane season exceed losses of previous and subsequent periods by far. Therefore, while areas affected by Hurricane Katrina, Rita and Wilma are located in hurricane states where hurricanes are not uncommon, the extraordinary impact of the 2005 hurricane season suggests that a significant part of the occurred damages was unexpected.

[Figure 2]

2.2 Insurance payments and federal disaster assistance

The effect of natural disasters on households and institutions is mitigated through insurance payments and federal disaster assistance. Such support is significant, but cannot offset the huge losses from a natural disaster. This is especially so when the magnitude of a natural disaster is huge and unexpected as in the case of the 2005 hurricane season.

According to the Insurance Information Institute (2014), about 50% of losses from the 2005 natural disasters were insured. The American Insurance Services Group (AISG) estimates that Katrina is responsible for $41.1 billion of insured losses in the United States (National

Hurricane Center, 2005). As a consequence of these unprecedented losses, insurance prices in catastrophe-prone areas were expected to rise and insurance terms and conditions were expected to be tightened, "as insurers seek to control their aggregate hurricane exposure" (Towers Watson, 2005). Hence, in addition to the immediate losses from the 2005 hurricane season, individuals and firms in affected areas were also facing more expensive and restricted insurance contracts, which made it more difficult to protect against potential disasters in the future.

In addition to potential insurance payments, the federal government of the U.S. offers assistance and funding through a variety of agencies and programs. In order to coordinate the response to a disaster, the *Federal Emergency Management Agency* (FEMA) was created in 1979. Following the announcement of a *Presidential Disaster Declaration*, FEMA's disaster assistance programs provide assistance to individuals ("individual assistance"), jurisdictions ("public assistance") and funds for "hazard mitigation".[5] Individual assistance is directed to individuals and families whose property has been damaged and whose losses are not covered by insurance. Public assistance supports state or local governments to rebuild a community's damaged infrastructure, which includes "debris removal, emergency protective measures and public services, repair of damaged public property, loans needed by communities for essential government functions and grants for public schools"(FEMA, 2015). Funds for hazard mitigation are used to "assist communities in implementing long-term measures to help reduce the potential risk of future damages to facilities" (U.S. Government Accountability Office, 2012). The majority of federal assistance is funded through FEMA's *Disaster Relief Fund*, which made obligations of roughly $40 billion with respect to damages caused by Hurricane Katrina (U.S. Government Accountability Office, 2012).

[5] Other minor categorizes are "mission assignments" and "administration" (U.S. Government Accountability Office, 2012).

2.3 Implications for the economy

Despite financial support through insurance payments and federal disaster assistance, the 2005 hurricanes were expected to have "substantial and long-term effects on the economies of southern Louisiana and Mississippi" (Congressional Research Service, 2005). The left graph of Figure 3 depicts the number of initial jobless claims filed in Louisiana between 2000 and 2009.[6] It shows a significant increase in the third and fourth quarters of 2005, mirroring the desolate situation during the 2005 hurricane season. The right graph illustrates the development of the CredAbility Consumer Distress Index in Louisiana, which is published by the St. Louis Fed and measures the financial condition of the average consumer. The index incorporates various data including employment, housing, credit scores, household budget and net worth.[7] A higher measure of the index mirrors a more favorable situation of the average household. The index shows the dramatic consequences for the financial situation of Louisiana households right after the 2005 hurricane season: an all-time low in the fourth quarter of 2005, even below the levels during the recent financial crisis.

[Figure 3]

Previous research also points to the adverse effects of hurricanes on local economic conditions. For example, Strobl (2011) studies hurricanes in the U.S. over the period 1948 to 2005 and finds a 0.45 percentage point decline of economic growth rates in affected counties. Deryugina et al. (2014) show that Katrina victims' face an initial negative wage income shock one year after the disaster but also that the gap in wage income disappears two years after the storm.

Summing up, the 2005 hurricane season caused significant uninsured losses and – at least temporary – a significant deterioration of local economic conditions. Moreover, this created

[6] The source for the number of initial jobless claims is the FRED online database of the St. Louis Fed (http://research.stlouisfed.org/fred2/).

[7] For details, see http://research.stlouisfed.org/fred2/release?rid=260. Note that the index was discontinued in 2013.

uncertainty how households and the economy would recover from the disaster.

3 Identification strategy and data

This sections starts with a description of our identification strategy. The following subsections provide detailed information on the characteristics of our sample.

3.1 Identification of affected and unaffected counties and banks

Following Hurricane Katrina and the contemporary Hurricanes Rita and Wilma in the second half of 2005, FEMA designated 135 out of 534 counties in the Gulf Coast region (Louisiana, Mississippi, Texas, Florida and Alabama) as eligible for individual and public disaster assistance.[8] We classify these counties as affected by the 2005 hurricane season (dark-grey shaded region in Figure 4). Correspondingly, we classify a bank as affected if its headquarter is located in an affected county. Next, we classify a county as unaffected if it is not eligible for public or individual disaster assistance and located in the U.S. Gulf Coast region or a neighboring state (light-grey shaded area in Figure 4). Banks with their headquarters in these counties are also classified as unaffected. Last, we exclude counties that are eligible for public disaster assistance but not eligible for individual disaster assistance – as well as banks with their headquarters in these counties – because this criterion is ambiguous. For example, counties in the northwest Texas region were very distant from the wind fields, but designated for public assistance. A possible reason is that they were affected indirectly through the accommodation of disaster evacuees or other minor effects. To guarantee that we are dealing with banks and counties that were clearly affected or clearly not affected by the hurricanes, we exclude these counties and banks. Consequently, we are left with a clean identification of affected and unaffected counties

[8]Source: https://www.fema.gov/disasters.

and banks.

[Figure 4]

3.2 Data sources and sample description

Our data come from several public sources. As regards the impact of the 2005 hurricanes (Katrina, Rita and Wilma) on the U.S. Gulf Coast region, we use data from the FEMA, as described above. Our bank data come primarily from the *Statistics on Depository Institutions* database of the *Federal Deposit Insurance Corporation* (FDIC).[9] This data set includes quarterly balance sheet and income data of all FDIC-insured U.S. banks. We also use bank-level data on mortgage inquiries from bank customers, which are available from the *Federal Financial Institutions Examination Council* (FFIEC) and reported by banks under the *Home Mortgage Disclosure Act*[10], to control for credit demand before and after the 2005 hurricanes. Data on banks' lending transactions comes from the *U.S. Small Business Administration* loan program (SBA)[11]. Finally, we use income and unemployment data at the county level from the *Bureau of Economic Analysis* (BEA)[12] and the *Bureau of Labor Statistics* (BIS)[13].

Bank sample. For our main bank-level analysis, we restrict the sample to banks located in the U.S. Gulf Cost region or neighboring states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Oklahoma, Tennessee and Texas.[14] This preliminary sample consists of 2,583 banks doing business at the end of the second quarter of 2005, i.e., the quarter before the hurricanes hit the U.S. Gulf Coast. Further, for our baseline sample,

[9] Source: https://www2.fdic.gov/sdi/index.asp.
[10] Source: http://www.ffiec.gov/hmda/.
[11] https://www.sba.gov/category/lender-navigation/sba-loan-programs
[12] Source: https://www.bea.gov/
[13] Source: http://www.bls.gov/lau/.
[14] In a set of robustness regressions, we also use a sample of banks from both narrower and wider geographic areas (see Subsection 4.1 and Table O-1).

we only consider banks that do not belong to a bank holding company, what we refer to as independent banks, which results in a preliminary sample of 706 banks.[15] These independent banks share features with community banks discussed by DeYoung et al. (2004) and are a viable part of the U.S. banking sector. We only consider independent banks in our baseline regressions because, at first, we want to exclude effects from internal capital markets within bank-holding groups that are due to capital allocations or implicit and explicit guarantees (Houston et al., 1997; Froot and Stein, 1998). We include both independent banks and banks that are part of a bank holding company in a set of extended regressions evaluating effects of internal capital markets.

Earlier studies that also use FDIC data point out that some of the data are erroneous or include rather atypical institutions. Therefore, similar to Berger and Bouwman (2009), we exclude banks that (1) have no commercial real estate or commercial and industry loans outstanding; (2) have zero or negative equity capital; (3) hold assets below $25 million, or (4) hold consumer loans exceeding 50% of gross total assets. We also leave out atypical institutions with risk-based capital ratios above 40%, which represents five times the regulatory requirement of 8%. This reduces the sample to 532 banks. Since we want to exclude biases from newly founded banks, we require banks' existence two years before the third quarter of 2005, which leaves us with a sample of 422 banks. Finally, as described in the previous section, we only consider banks that are located in a county that was clearly affected or clearly not affected by the 2005 hurricane season, which results in our final sample of 258 banks, of which 94 were affected and 164 are unaffected by the 2005 hurricane season.

When we include banks that are part of a bank holding company in our analysis, the sample is extended to a total of 1253 banks, of which 307 were affected and 946 were unaffected by the hurricanes. When we use loan transaction data from the SBA loan program, data is only available for a subset of banks, which restricts the sample to 337 independent and

[15] Technically, we require that the FDIC data field namehcr, which denotes a bank-holding company, is left blank.

BHC banks, of which 73 were affected and 264 were unaffected by the hurricanes.

County sample. We use county-level data to assess whether the structure of the banking system matters for local economic developments after Hurricane Katrina. This sample is based on a propensity score matching procedure, which requires that counties in the treatment and control group have similar characteristics before the 2005 hurricane season. In particular we match affected and unaffected counties conditional on their average total personal income in US$, the number of employed persons, the number of unemployed persons, and the unemployment rate in 2004 (1:1 nearest-neighbor matching with a caliper of 0.01). This procedure results in a sample of 176 counties in the U.S. Gulf Coast region and neighboring states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, Oklahoma, Tennessee, Texas).

3.3 Variables description and summary statistics

Our main explanatory variable is the exogenous adverse shock on banks' asset quality caused by Hurricane Katrina, Rita and Wilma in Q3 and Q4 2005. Asset quality reflects the "quantity of existing and potential credit risk associated with the loan and investment portfolios, other real estate owned, and other assets, as well as off-balance sheet transactions" (Federal Reserve Board, 2014). The 2005 hurricanes caused significant unexpected losses and increased credit risks for banks in affected regions. We are thus able to identify a causal relation between asset quality and our dependent variables. Measures for asset quality, which are frequently used in the literature, are risk-weighted assets (Avery and Berger, 1991), the standard deviation of the return on assets or the standard deviation of (unlevered) stock price returns (Gropp and Heider, 2010; Flannery and Rangan, 2008). In our study, we circumvent using these traditional measures, which cause endogeneity concerns, because banks typically determine their asset quality and capital ratio simultaneously.

The dependent variable that we use in our baseline regressions is a bank's quarterly risk-based capital ratio.[16] We thereby explore how banks adjust their risk-based capital ratios during the two year period following the 2005 hurricane season. The banks in our sample operate in a Basel I regulatory environment. Consequently, they can assign risk weights corresponding to five different categories that range from zero to 100%. For example, U.S. government securities have a risk weight of zero, residential mortgage loans have a risk weight of 50%, and commercial and industrial loans have a risk weight of 100%. Banks are required to hold capital equal to at least 8% of risk-weighted assets.

Other dependent variables used in this study, which allow us to explore the mechanisms how banks adjust their capital ratios and business decisions, are total capital, risk-weighted assets, U.S. government securities, real estate loans, real estate commercial loans, reconstruction and development loans, consumer loans and commercial and industrial loans. For some specifications, we use the regional unemployment rate from the county where a bank has its headquarters to control for time-varying differences in local economic conditions.

Further, we consider a bank's volume of approved small business loans that is reported under the SBA loan program. This data reflects new lending transactions and thus complements the analysis of banks' balance sheet exposures. In particular, we consider the total volume of a bank's gross SBA lending as well as the volume net of government guarantees from the SBA program.

Finally, we are interested in the role of the structure of local banking systems for economic development. We therefor consider per county j the share of banks belonging to a bank holding company ($BHCshare_j$) and the average of banks' risk-based capital ratios ($CAPaverage_j$). Both measures are based on all banks with a branch in county j before the 2005 hurricane season (June 2005). The data on bank branches comes from the *Summary of Deposits* database of the FDIC, and the data on economic developments on

[16] Risk-based capital ratios are equivalent to the sum of the bank's Tier 1 and Tier 2 capital divided by its risk-weighted assets. For some banks, the nominator also includes Tier 3 capital allocated for market risk, net of all deductions. For details, see "Schedule RC-R – Regulatory Capital" of the FDIC.

county level comes from the Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS). As measures of economic activity on the county level, we use total personal income, the number of employed and unemployed persons, and the unemployment rate per county.[17]

For a description of all variables used in this study, see Table 1.

[Table 1]

Summary statistics are provided in Table 2. All statistics refer to the average values of the two year period before the 2005 hurricane season, i.e., Q3 2003 to Q2 2005 for the bank sample based on quarterly data, and 2003 and 2004 for the county sample based on yearly data. The table reports mean values and standard deviations separately for the groups of affected banks (or counties) and unaffected banks (or counties), as well as normalized differences, which we discuss in more detail below.

[Table 2]

3.4 Similarity between treatment and control group

It is important for the validity of the difference-in-difference estimation that banks in our treatment group (affected banks) and banks in our control group (unaffected banks) have similar characteristics before the event. As suggested by Imbens and Wooldridge (2009), we report summary statistics with normalized differences to compare the similarity between both groups as regards important bank characteristics.[18] As a rule of thumb, groups are

[17]Another useful measure for our analysis would be the gross domestic product (GDP) by county, i.e., the value of production that occurs within the geographic boundaries of a county. However, GDP by county is not available (the smallest geographic area for which it is available is a metropolitan area).

[18]Normalized differences are calculated as "the difference in averages by treatment status, scaled by the square root of the sum of the variances" (Imbens and Wooldridge, 2009, p. 24).

regarded as sufficiently equal and adequate for linear regression methods if normalized differences are largely in the range of ± 0.25.

The summary statistics reported in Table 2 confirm that the groups of affected and unaffected banks are relatively similar before the event. In particular, banks in both groups hold, on average, similar levels of risk-based capital ratios of around 17% during the two years prior to the 2005 hurricane season. Normalized differences of 0.037 are clearly in the range of ± 0.25. Note that the level of 17% substantially exceeds the regulatory minimum of 8%. This observation is in line with Flannery and Rangan (2008), who also report relatively high ratios for U.S. banks. We also find for all reported bank-level variables, with the exception of consumer loans, that normalized differences are in the range of ± 0.25.

At the county level, we find that all statistics are relatively similar for affected and unaffected counties. Normalized differences are clearly in the range of ± 0.25.

Overall, we find that characteristics of affected and unaffected banks and counties are similar before the event and, hence, that the treatment and control groups are well suited for our analysis.

4 Empirical analysis

In this section we explore how a deterioration in banks' asset quality through the 2005 hurricane season affects banks' capital ratios, asset allocation and lending decisions in the aftermath of the hurricanes. In our analysis we are interested whether and how different levels pre-Katrina capital levels affect banks' behavior. Our analyses also includes an assessment of the role of bank structure for these developments. Furthermore, we are interested in the macroeconomic impact of the disaster, in particular how unemployment and growth developed in the post-Katrina environment in counties with different structures of the banking system.

Anecdotal evidence on the deterioration in banks' asset quality following the disaster is provided by the FDIC and rating agencies, as noted in the introduction of this paper (see, e.g., the quote from the FDIC on page 3). Empirical evidence on the adverse short-term effects of the hurricanes on bank profitability and bank stability is provided in Appendix C of this paper highlighting the adverse effects of the hurricane season on banks' stability and profits.[19]

4.1 Do affected banks adjust their risk-based capital ratios?

In this section we explore whether independent banks' risk-based capital ratios change after these banks experience an adverse shock on their asset quality through the 2005 hurricane season.

Baseline estimation. For the empirical analysis we need to consider potential parallel macroeconomic and industry-wide factors that affect all banks independent of the shock. Another concern is that unobservable bank characteristics might influence the analysis. To account for both aspects, we use a difference-in-difference estimation technique with time and bank fixed effects. Formally, we estimate the following equation with a fixed effects OLS model for a sample period of two years around the 2005 hurricane season (Q3 and Q4 2005):

$$\text{CAP}_{it} = \nu_i + \tau_t + \beta_1(\text{Event}_t \times \text{Affected}_i) + \epsilon_{it}. \tag{1}$$

The dependent variable CAP_{it} is the risk-based capital ratio of bank i at time t. The terms ν_i and τ_t represent bank fixed effects and yearly time fixed effects, respectively. The variable $Event_t$ is a time dummy with a value of zero for the eight quarters before the hurricanes ($t \leq$ Q2 2005) and a value of one for the eight quarters after the hurricanes ($t \geq$ Q1 2006).

[19] The adverse effects of natural disasters on bank stability are also shown by Noth and Schüwer (2017) for a sample of 6,136 U.S. banks over the period 1994 to 2012.

The variable $\textit{Affected}_i$ is a dummy variable of bank i that is one if the bank is located in a county classified by FEMA as eligible for "public and private disaster assistance" and thus belongs to the treatment group, and zero otherwise (for the control group). Hence, the interaction term $\textit{Event}_t \times \textit{Affected}_i$ is one if both the variable $\textit{Event}_t$ and the variable $\textit{Affected}_i$ amount to one, and zero otherwise. The corresponding coefficient β_1 is the main interest. It shows how affected banks adjust their risk-based capital ratios after the event relative to the control group. The single terms $\textit{Event}_t$ and $\textit{Affected}_i$ do not appear in the equation because they are absorbed by the time and bank fixed effects, respectively. The term ϵ_{it} represents the idiosyncratic error term. Standard errors are clustered at the bank level.

For robustness, we reestimate our baseline estimation with three alternative specifications. First, we estimate Equation (1) without bank fixed effects. The variable Affected_i, which otherwise interferes with bank fixed effects, then enters the equation.

Second, we consider potential concerns that a shortfall in credit demand in affected regions may drive our results. Technically, such a shortfall may lead to lower risk-weighted assets and consequently higher risk-based capital ratios of affected banks. However, a shortfall in credit demand is unlikely because of reconstruction activities. As stated by the Federal Reserve Bank of Atlanta (2005), credit demand was rather expected to increase in affected regions in the aftermath of the 2005 hurricanes. Nevertheless, we add a control variable for banks' credit demand in a robustness specification. The general difficulty for such a control variable is that it needs to disentangle credit demand from credit supply. Therefore, a bank's reported loan volume is not suitable. However, we can use data reported by banks under the *Home Mortgage Disclosure Act* to build a proxy for credit demand. In particular, banks are required under this act to report the volume of all mortgage applications on a yearly basis. We use this data to calculate $\text{Credit demand}_{i\gamma}$ per bank i and year γ as the log of the dollar volume of each bank's mortgage applications (accepted and denied mortgages). We then include the variable $\text{Credit demand}_{ij}$ in Equation (1). Note that this reduces our sample from 258 to 182 banks, because the data is not available for all banks.

Third, we estimate Equation (1) with further control variables which are common in the banking literature. In particular, we add the return on assets (*RoA*), the ratio of non-performing loans to assets (*NPL/Assets*) and the log of the total number of employees (*Bank size*).[20] Note that these control variables only matter for the estimation to the degree that they are time variant because they are otherwise already included in the bank fixed effects. Further, to capture differences in local economic developments, we use quarterly unemployment rates at the county level as an additional time-varying control variable.

Baseline results. We present our baseline results in Table 3. Column (1) shows the difference-in-difference estimation with bank fixed effects and without further covariates, as reflected in Equation (1). With regard to our main variable of interest, the interaction term *Event*×*Affected*, we observe a positive and significant coefficient that shows that affected banks increase their capital ratios after the hurricane relative to the control group. This effect is also economically significant. The risk-based capital ratio of affected banks increases on average by 1.04 percentage points, as shown by the point estimate of the interaction term.

Column (2) shows results for our baseline estimation of Equation (1) without bank fixed effects. The results remain robust and confirm the relatively higher risk-based capital ratios of banks after the event. The average effect of the hurricanes on banks' risk-based capital ratios, which is reflected in the coefficient of the interaction term β_2, is 1.49 percentage points and in the same range as before.

Next, we again include bank fixed effects as well as a proxy for credit demand in the regression. We find that results remain intact. The effect on banks' capital ratios, as reflected in a β_2 of 1.24 percentage points, is again in the range of estimation results in

[20]Results remain qualitatively the same if we use the log of total assets instead of the log of total number of employees for bank size or RoE instead of RoA.

Column (1).

Finally, we add bank characteristics that are regarded as relevant for banks' capital ratios as well as the unemployment rate in a bank's home county to control for macroeconomic developments. We find that banks' risk-based capital ratios decreases in bank size, but are not significantly affected by the other new covariates. Importantly, the coefficient of the interaction term which is our main interest, remains in the same range as before.

[Table 3]

Summing up, this set of results strongly advocates that independent banks react when confronted with an adverse shock on their asset quality. They do this by increasing their risk-based capital ratio relative to banks that do not experience this shock. The results suggest that banks thereby strengthen their cushion against insolvency.

This finding adds to Flannery and Rangan (2008) who suggest that a change in the banking environment rather than supervisory pressure leads to higher capital ratios for U.S. banks during the 1990s. Similarly, Gropp and Heider (2010) argue that banks rely on their "own judgement" to define the appropriate amount of total risk-based capital and that regulatory requirements are of second-order importance.

Alternative regional samples. In the following, we discuss results of several robustness regressions. The respective results tables are provided in an online appendix. The first robustness check examines whether a smaller or larger sample of the states that we consider for the composition of the control and the treatment groups might change our main results. Recall that our main results are based on a sample with 94 affected banks and 164 unaffected banks in Alabama, Florida, Louisiana, Mississippi, Texas, Georgia, Tennessee, Arkansas and Oklahoma. To check robustness, we make the following changes: First, we restrict the sample to banks that only operate in Alabama and Florida. The reason is that only these states comprise both counties affected and counties unaffected by the hurricane. Second, we restrict the sample to counties in the core states affected by the hurricane (Louisiana, Mississippi, Florida, and Alabama) and thus exclude banks in neighboring states (Georgia, Tennessee, Arkansas, and Oklahoma) from the control group relative to our baseline sample. Third, we extend the sample to banks in Texas.

We rerun our main regression and provide results for our baseline sample and the three alternative regional samples in Table O-1. Across all groups we find significant results for the treatment effect from Hurricane Katrina on the risk-based capital ratio of affected banks. We also find that the effect is economically stronger for the Alabama and Florida region (Column (1)). Here, affected banks increase their risk-based capital ratio by 2.28 percentage points relative to their unaffected peers after the event. Overall, Table O-1 shows that our results do not hinge on the choice of a specific regional sample or control group.

Extended control group or treatment group. As stated in Subsection 3.1, the treatment group includes banks with their headquarter in a county eligible for individual and public disaster assistance. The control group includes banks with their headquarter in a county not eligible for disaster assistance. For robustness we do two exercises: First, we include to the control group all banks with their headquarter in a county in the U.S. Gulf Coast region or neighboring states that we previously ignored, because these counties were not eligible for individual but only for public disaster assistance. Thus, we add to the control group banks located in counties that are somehow affected by the hurricanes, but certainly less than counties that were also eligible for individual disaster assistance. Second, we include these banks to the treatment group instead of to the control group. For both exercises, the sample increases from 258 to 422 independent banks. As shown for regressions with the extended control group and for regressions with the extended treatment group ((Columns (1) to (4) and Columns (5) to (8), respectively, of Table O-2), results are qualitatively unchanged compared to the baseline regressions in Table 3. As expected, the coefficients of $Event \times Affected$ are relatively smaller in all regressions, because the extended control group and the extended treatment group are more fuzzy compared to the baseline sample.

Parallel-trend assumption. To alleviate potential biases we have to guarantee that the parallel-trend assumption prior to the treatment is satisfied. In other words, the risk-based capital ratios should follow a similar trend for the treatment and control groups. Analogous to previous studies, in Figure 1 we graphically inspect the trend of mean total risk-based capital for both groups and confirm the parallel-trend assumption. Further, as already discussed in Subsection 3.3 and shown in Table 2, the groups of affected and unaffected banks are largely similar with respect to common bank characteristics.

Collapsed sample. In order to show that the results are robust against problems with difference-in-difference techniques in the presence of serial correlation, Bertrand et al. (2004) suggest ignoring the time structure of the data. Therefore, we average the data before and after the hurricane and rerun the estimation for this collapsed sample. As before, standard errors are clustered on bank level. Table O-3 presents results for the collapsed sample. We find the treatment effect for all different periods intact and in the range of 1.12 to 2.03 percentage points.

Time-placebo estimation. The possibility that the results are driven by time trends unrelated to Hurricane Katrina needs to be ruled out. Therefore, we run a "placebo estimation" where the treatment shifts from the time period when Hurricane Katrina, Rita and Wilma actually occurred (Q3 and Q4 of 2005) to a time period three years earlier (Q3 and Q4 of 2002). We then rerun the estimation for observations two years before and after this "2002 pseudo hurricane" event. As before, we run the regressions using total risk-based capital as the dependent variable for four specifications: (1) with bank fixed effects; (2) without bank fixed effects; (3) with bank fixed effects controlling for credit demand;

and (4) with bank fixed effects controlling for demand and some additional covariates that are common in the literature. Table O-4 shows the results for this analysis, which can be directly compared to our baseline results in Table 3. We do not find an effect for the 2002 pseudo hurricane in any of the specifications. This finding supports our assumption that our results are not driven by factors unrelated to Hurricane Katrina.

4.2 The role of bank capitalization for capital ratio adjustments

Bank capitalization is a key determinant of bank risk in the supervisory assessment. Banks with low capital ratios are considered as less stable than banks with high capital ratios.[21] In this section we are interested in whether banks with lower or higher capital ratios before Hurricane Katrina struck the U.S. Gulf Coast, i.e., banks that are considered less stable or more stable by the banking supervisor, differ in their capital ratio adjustments after the hurricanes.

We construct a bank's initial pre-Hurricane Katrina risk-based capital ratio by calculating for each bank the mean value of its risk-based capital ratio over the eight quarters before Hurricane Katrina (Q3 2003 to Q2 2005). These capital ratios range from 9.2% to 37.8% with a mean of 17.2%). Note, that more than 95% of banks held an average pre-Katrina risk-based capital ratio above 10%, which is well above the required 8% and considered as "well capitalized" by the FDIC. The initial risk-based capital ratio allows us to separate banks into two groups: banks with an initial risk-based capital ratio below the median ($preCAP$=0) or above the median ($preCAP$=1). Then, we extend Equation (1) by interacting the variables Event and $Event \times Affected$ with $preCAP$. Formally, we estimate the

[21] Different capital ratios of banks are typically related to different business models, which can be more or less risky, and reflect aspects such as investment opportunities, bankruptcy costs, franchise value, value of deposit guarantees and bank governance.

following equation for the sample of independent banks with a fixed effects OLS model:

$$\begin{aligned}\text{CAP}_{it} = \nu_i + \tau_t + \beta_1(\text{Event}_t \times \text{Affected}_i) + \beta_2(\text{Event}_t \times \text{preCAP}_i) \\ + \beta_3(\text{Event}_t \times \text{Affected}_i \times \text{preCAP}_i) + \epsilon_{it}.\end{aligned} \tag{2}$$

The first coefficient of interest is β_1 and refers to *Event*$\times$*Affected*, which now shows how a bank with a below median pre-Hurricane Katrina capital ratio adjusts its capital ratio after the hurricanes relative to the control group. The second coefficient of interest is β_3 and refers to *Event*$\times$*Affected*$\times$*preCAP*, which shows whether (and how) the previous effect differs across the two groups of banks. As before, we run the regressions using risk-based capital ratios as the dependent variable for four specifications: (1) with bank fixed effects, (2) without bank fixed effects, (3) with bank fixed effects controlling for credit demand; and (4) with bank fixed effects controlling for credit demand and some additional covariates.

As shown in Column (1) of Table 4, the coefficient of the interaction term *Event*$\times$*Affected* is positive but insignificant with a value of 0.0009. This means that affected banks with a low pre-Hurricane Katrina capital ratio do not significantly increase their risk-based capital ratio after the event relative to the control group (unaffected banks with the a low pre-Hurricane Katrina capital ratio). When we consider whether this effect is significantly different for the group of banks with a high pre-Hurricane Katrina capital ratio, we observe a positive and significant coefficient of the triple interaction term *Event*$\times$*Affected*$\times$*preCAP*. Hence, the effect *Event*$\times$*Affected* is significantly different across the two groups of banks. At the bottom of Table 4 we show that banks with a high pre-Hurricane Katrina capital ratio increase their risk-based capital ratios by 1.87 percentage points relative the group of banks with a low pre-Hurricane Katrina capital ratio. This suggests that the key message of the previous regressions that banks in disaster areas increase their risk-based capital ratios after the hurricanes mainly comes from banks that are relatively high-capitalized. This finding also holds for the OLS estimation in Column (2), the fixed-effects estimation that controls for credit demand in Column (3), and for the fixed-effects estimation with additional control variables in Column (4).

[Table 4]

The analysis yields an interesting result about how different banks react to the adverse shock on their asset quality through the hurricanes. Banks that appear ex ante relatively conservative in their business model – or at least hold relatively large capital buffers – also react conservatively to the shock and further increase their buffers against future losses. The effect becomes smaller and insignificant for banks that appear more risky in their business model – or at least hold relatively smaller capital buffers. From the perspective of the supervisor, these banks are presumably those that should increase their buffers against future losses, but as our evidence shows, these banks are not capable or not willing to do so.

4.3 The role of bank structure for capital ratio adjustments

In this section we explore whether banks that are part of a bank holding company, which we refer to as BHC banks, adapt their capital ratios in a similar way than independent banks, which the analysis focused on so far. Contrary to independent banks, bank holding companies have the opportunity to establish internal capital markets to allocate capital across their various subsidiaries (Houston et al., 1997). As a consequence, BHC banks have greater leeway in case of financial distress and may rely on this flexibility instead of building higher capital ratios by themselves.

For the following analysis, we extend the sample of 258 independent banks by 995 BHC banks. This results in a total sample of 1,253 banks, of which 307 were affected by the 2005 hurricanes and 946 were unaffected.

Formally, we extend Equation (1) to differentiate between independent banks and BHC banks and estimate the following equation:

$$\begin{aligned}\mathrm{CAP}_{it} = \nu_i + \tau_t + \beta_1(\mathrm{Event}_t \times \mathrm{Affected}_i) + \beta_2(\mathrm{Event}_t \times \mathrm{BHC}_i)\\ + \beta_3(\mathrm{Event}_t \times \mathrm{Affected}_i \times \mathrm{BHC}_i) + \epsilon_{it}.\end{aligned} \tag{3}$$

The variable *BHC* has a value of 0 for independent banks and a value of 1 for BHC banks. As in the previous paragraph with banks that were low- or high-capitalized, we estimate a difference-in-difference-in-difference model that analyses whether the effect on affected independent banks (relative to before the hurricanes and relative to unaffected independent banks) is different from the effect on affected BHC banks (relative to before the hurricanes and relative to unaffected BHC banks). In particular, the interaction term *Event×Affected* captures the effect of the 2005 hurricanes on independent banks, and the the coefficient of the triple interaction term *Event×Affected×BHC* captures whether and how the effect is different for BHC banks.[22]

As before, we run the regressions using total risk-based capital as the dependent variable for four specifications: (1) with bank fixed effects as reflected in the equation above; (2) without bank fixed effects; (3) with bank fixed effects controlling for credit demand; and (4) with bank fixed effects controlling for credit demand and some additional covariates that are common in the literature.

As shown in Column (1) of Table 5, we find that the coefficient of the triple interaction term, which shows the differential effect for BHC banks, is significant and negative. The magnitude of this coefficient of -0.0089 is also very close to the magnitude of the coefficient of the double interaction term of 0.0104. Hence, the total effect is 0.0014 for BHC banks (*BHC*=1) while it is 0.0104 for independent banks (*BHC*=0). The bottom rows of Table 5 contrast these effects for both groups of banks and also show the respective standard errors. Accordingly, the effect is significant for independent banks on the 5% level and insignificant

[22] Again, note that the terms BHC and Affected×BHC are captured by the bank fixed effects and are therefore not included in the equation.

for BHC banks. Results remain robust when we estimate the equation without bank fixed effects (Column (2)), control for credit demand (Column (3)) or include additional bank covariates (Column (4)).

[Table 5]

In summary, we observe that affected independent banks adjust their risk-based capital ratios after the event while affected banks that belong to a bank holding company do not. This indicates that BHC banks rely on potential financial support from their bank holding company, which they can access through internal capital markets and, therefore, do not build up precautionary capital reserves internally. Our evidence adds to findings of Cortes and Strahan (2017) who show that banks that are affected by natural disasters and belong to a bank holding company benefit from this structure in the sense of not needing to act precautionary.

4.4 Development of banks' balance sheet exposures

Next, we are interested in the mechanisms how banks adjust their risk-based capital ratios. We therefore explore the development of banks' balance sheet exposures, including banks' capital, risk-weighted assets, U.S. government securities and different loan categories. Further, we consider the previous results that banks' risk-based capital ratios before Hurricane Katrina as well as bank structures matter. Hence, we include interactions with both dummy variables that were introduced in the previous sections, *preCAP* and *BHC*, in the regression model:

$$\begin{aligned}
\mathrm{Y}_{it} = {} & \nu_i + \tau_\gamma + \beta_1(\mathrm{Event}_t \times \mathrm{Affected}_i) + \beta_2(\mathrm{Event}_t \times \mathrm{BHC}_i) + \beta_3(\mathrm{Event}_t \times \mathrm{preCAP}_i) \\
& + \beta_4(\mathrm{Event}_t \times \mathrm{Affected}_i \times \mathrm{BHC}_i) + \beta_5(\mathrm{Event}_t \times \mathrm{Affected}_i \times \mathrm{preCAP}_i) \qquad (4) \\
& + \beta_6(\mathrm{Event}_t \times \mathrm{BHC}_i \times \mathrm{preCAP}_i) + \beta_7(\mathrm{Event}_t \times \mathrm{Affected}_i \times \mathrm{BHC}_i \times \mathrm{preCAP}_i) + \epsilon_{it}.
\end{aligned}$$

Y_{it} stands for alternative balance sheet variables: total capital over total assets, risk-weighted assets over total assets, government securities over total assets, real estate loans over total assets, real estate commercial loans over total assets, real estate construction and development loans, consumer loans over total assets, and consumer and industry loans over total assets. All other variables are defined as before in Equations (1) to (3).

Regression results are shown in Table 6. The bottom of the table shows corresponding difference-in-difference effects (*Affected*×*Event*) for the four different groups of banks: independent and low-capitalized (*BHC*=0 and *preCAP*=0), independent and high-capitalized (*BHC*=0 and *preCAP*=1), BHC and low-capitalized (*BHC*=1 and *preCAP*=0), and BHC and high-capitalized (*BHC*=1 and *preCAP*=1).

To recap our previous results, the first column of Table 6 shows regression results of Equation (4) using banks' risk-based capital ratio (*RBCR*) as dependent variable. We again find that in particular independent banks banks with relatively high pre-Hurricane Katrina risk-based capital ratios (*BHC*=0 and *preCAP*=1) significantly increase their risk-based capital ratios. The increase for this group of banks is 1.87 percentage points. We also find a significant increase for the group of BHC banks with relatively low pre-Hurricane Katrina risk-based capital ratios (*BHC*=1 and *preCAP*=0), but the increase is much smaller (0.39 percentage points).

Total capital. The second column of Table 6 shows regression results using the natural logarithm of total capital as dependent variable. We find no significant effect for any of the four groups of affected banks, which indicates that our baseline results are not driven by a change in banks – not risk-adjusted – capital ratios.

Risk-weighted assets. Next, we use the natural logarithm of risk-weighted assets as dependent variable in the regression. Results in Column (3) of Table 6 show a significantly negative coefficient of the interaction term for the group of independent banks with a high initial risk-based capital ratio (*BHC*=0 and *preCAP*=1), i.e., a decrease of 8.45 percent. This suggests that these banks achieve higher risk-based capital ratios after Hurricane Katrina, as documented in Column (1), by reducing their exposure to risky assets.

In the following, we explore different asset categories that determine banks' risk-weighted assets. In particular, U.S. government securities have a risk-weight of zero, real estate loans have a risk-weight between 50% and 100% (e.g., typically 50% for loans to individuals or families and 100% for commercial real estate loans), consumer loans as well as commercial and industrial loans have a risk-weight of 100%.

U.S. government securities. Regression results with the natural logarithm of U.S. government securities as dependent variable are shown in Column (4) of Table 6. Again, we find a significant and most pronounced effect for independent banks with a relatively high pre-Hurricane Katrina risk-based capital ratio (*BHC*=0 and *preCAP*=1). These banks increase their holdings of government securities by 42.5 percent after the 2005 hurricane season relative to the control group. We also find a significant and positive increase of 21.3 percent for the group of BHC banks that are relatively low capitalized (*BHC*=1 and *preCAP*=0).

Different loan categories. We now take a closer look at exposure to different loan categories: real estate loans (*RE loans*), commercial real estate loans (*RECO loans*), reconstruction and development loans (*RECON loans*), consumer loans (*CON loans*), and commercial and industrial loans (*C&I loans*). We do not find significant difference-in-difference effects (*Affected*×*Event*) for the first four loan categories, but for C&I loans. In particular, affected independent banks with a relatively high pre-Hurricane Katrina risk-based capital ratio (*BHC*=0 and *preCAP*=1) decrease their exposure to C&I loans by 16.87 percent relative to unaffected banks, as shown at the bottom of Table 6. The effect is not significant for the other three subgroups of banks.

[Table 6]

Overall, the evidence in this section shows that effects of the 2005 hurricane season are most pronounced for independent banks with relatively high pre-Hurricane Katrina risk-based capital ratios. These banks decrease their risk-weighted assets, which is explained by increased exposures to U.S. government securities and decreased exposures to commercial and industrial loans relative to the control group.

4.5 Banks' lending activities

Results in the previous section lead to the question whether declines in commercial and industrial (C&I) loan exposures of independent and highly capitalized banks are driven by a reduction in lending or other strategies relative to the control group. To shed more light on this issue, this section provides evidence on banks' new lending transactions before and after the 2005 hurricane season.

The data for this analysis comes from the *U.S. Small Business Administration* (SBA) 7(a) loan program data set, which provides lending transaction data including bank name, borrower name and location, date and approved lending volume.[23] The SBA typically provides guarantees on parts of the loans in order to strengthen access to finance for small businesses. Information about the gross approved lending volume and the SBA guaranteed part – in most cases between 50 and 75 percent – is also included in the data set. Borrowers may use such loans to establish a new business or to expand an existing business. Importantly, the loans are made through financial institutions, which assess whether borrowers are financially eligible, use the funds for a sound business purpose and fulfill all other requirements of the program.[24] A restriction of this analysis is that not all

[23] See https://www.sba.gov/.

[24] Note that an alternative SBA program provides disaster loans, but these loans are approved and administered directly by the SBA and are hence not useful for our analysis.

banks are included in the SBA data set, which reduces the sample for this analysis from 1253 to 337 independent and BHC banks.

Estimation. The analysis differentiates between a bank's gross volume of approved SBA loans and the volume of SBA loans net of guarantees. Further, we differentiate between a bank's lending in its *core market* and *non-core market*. We define a bank's core market as all counties where a bank has established a branch as of June 2005 and all other counties as non-core markets.[25] This results in six variables on bank-year level: (1a) the total volume of a bank's gross SBA lending, (1b) the volume of a bank's gross SBA lending in its core market, (1c) the volume of a bank's gross SBA lending in its non-core market, (2a) the total volume of a bank's SBA lending net of guarantees, (2b) the volume of a bank's SBA lending net of guarantees in its core market and (2c) the volume of a bank's SBA lending net of guarantees in its non-core market. We then use the natural logarithm of these variables as dependent variables in a regression model equivalent to Equation (4).

Results. Regression results are shown in Table 7. The difference-in-difference effects ($Event \times Affected$) at the bottom of the table provide interesting results. We observe significant effects for the group of affected independent banks with relatively high pre-Katrina risk-based capital ratios (BHC=0 and $preCAP$=1), but not for the other groups. The former significantly increase total SBA lending as well as SBA lending in their core markets, but not in their non-core markets. These results are similar for gross SBA loans (Columns (1) to (3)) and SBA loans net of guarantees (Columns (4) to (6)).

A plausible explanation for this finding is that independent banks may be more focused on their core markets relative to BHC banks that are more diversified. They may be better able to collect and process information and have more incentives to do so. Empirical evidence

[25] This classification follows Cortes and Strahan (2017) who explore mortgage lending towards borrowers in banks' core markets and non-core markets following a natural disaster. Data on bank branching comes from the *Summary of Deposits* database of the FDIC (see https://www.fdic.gov/bank/statistical/).

by Berger et al. (2005) suggests that smaller banks have stronger relationships with their borrowers and alleviate credit constraints more effectively than larger banks. Berger et al. (2017) show that such comparative advantages of smaller banks over larger banks are even stronger when economic conditions are adverse. Further, Loutskina and Strahan (2011) find that more concentrated lenders are more active in information-sensitive segments of the mortgage market. The 2005 hurricane season caused massive destruction of property and uncertainty about the financial situation and business prospects of borrowers. Hence, information about the creditworthiness of borrowers was difficult to assess.[26]

Further, our results add to the existing evidence that bank capital is important for bank lending in times of crisis. In particular, relatively high capital ratios before the 2005 hurricane season are associated with relatively more SBA lending in the subsequent years.

[Table 7]

Interestingly, our evidence shows that affected banks that are independent and well-capitalized both *decrease* their exposure to C&I loans (Subsection 4.4) and *increase* their lending to small businesses in their core-markets (this section) relative to the control group. Hence, these banks reduce their risk-weighted assets, but not through reduced new lending. These banks presumably engage in loan sales or loan securitization. Unfortunately, such data is very limited for C&I loans of independent banks, so that we cannot test this directly. However, a related study by Chavaz (2016) analyses mortgage loans from the *Home Mortgage Disclosure Act* data set. The study finds that more local banks both originate a higher share and sell a higher share of these loans in the aftermath of Hurricane Katrina in 2005 compared to more diversified banks. Hence, it is also very plausible for our results that independent and well-capitalized banks at the same time increase new C&I lending in their core-markets and reduce balance sheet exposures to C&I loans through loan sales.

[26]Cortes and Strahan (2017) also provide evidence on the special role of banks' core markets. They explore how multi-market banks change their credit supply when local credit demand increases after natural disasters. They find that bank lending increases in affected markets and decreases in unaffected non-core markets, but not in unaffected core markets where banks have a branch presence.

4.6 Structure of the local banking system and economic development

Our previous results reveal that bank behavior in the aftermath of the 2005 hurricane season differs across banks depending on a bank's pre-hurricane capitalization and structure. This may have effects on the real economy. Hence, we explore in this section whether the structure of the local banking system matters for economic developments in counties affected by the 2005 hurricane season. Note that variation across local banking structures is not random because it develops jointly with the local economy. The following analysis thus provides evidence on the relation between banking structure and economic development, and not necessarily evidence on a causal effect of banking structure on economic development.[27]

Related research by Cortes (2014) shows that the presence of local lenders is beneficial for job creation after natural disasters. Further, studies by Cecchetti et al. (2011) and Jordà et al. (2017) suggest that a higher average bank capital ratio of a country's financial sector at the start of a financial-crisis recession is associated with a significantly stronger recovery after the crisis. The analysis in this section adds to this evidence.

The following analysis uses county-level data, in contrast to the bank-level analysis in the previous sections. Counties are classified as affected if they were designated for disaster assistance by FEMA, corresponding to the description in Subsection 3.1 (see also Figure 4). The economic development in affected and unaffected counties over the period 2003 to 2005 is illustrated in Fig 5. The left panel shows the development of the average log of total personal income. The graph does not reveal any significant effects of the 2005 hurricane season. Further, the right panel of Figure 5 shows the average unemployment rate in affected and unaffected counties over the sample period. Here, we can observe a significant increase in 2005 when the hurricanes hit the U.S. Gulf coast, as well as a significant

[27] Evidence on a causal effect would require exogenous variation in the structure of the local banking system, which is not the case for our analysis.

decrease in the following years. Note that the unemployment rate alone is an intricate measure because of migration effects in the aftermath of a natural disaster.[28] Hence, we also consider the number of employed persons, the number of unemployed persons, and the total labor force (sum of employed and unemployed persons) in the regression analysis.

[Figure 5]

As measures of the structure of the local banking system in county j, we consider the share of banks belonging to a bank holding company ($BHCshare_j$) and the average of banks' risk-based capital ratios ($CAPaverage_j$) for all banks with a branch in county j before the 2005 hurricane season (June 2005). The measures are calculated using a bank's sum of deposits by county – a proxy for a bank's local presence and business activities – as weights. Both variables are demeaned.[29] Consequently, the "average" county has values of $BHCshare_j = 0$ and $CAPaverage_j = 0$.

When we compare counties with a value of BHCshare (before demeaning) at the 25th and 75th percentiles, this corresponds to 74 percent and 100 percent of banks belonging to a bank holding company, respectively. Hence, a value of BHCshare at the 25th percentile can also be interpreted as a more diversified banking system relative to a value of BHCshare at the 75th percentile. The values of CAPaverage (before demeaning) at the 25th and 75th percentiles are 12.03 and 17.97 percent, respectively, for independent banks and 10.96 and 15.15, respectively, for BHC banks.

[28] For example, Boustan et al. (2012) document migration away from tornado-struck areas in the United States during the 1920s and 1930s, a period before coordinated public disaster assistance.

[29] In particular, we subtract the mean value of 85.94 percent across all counties to calculate the demeaned BHCshare. To calculate the demeaned CAPaverage, we first consider the different capital ratios of independent and BHC banks and subtract the mean value of 15.84 percent for all independent banks and the mean value of 13.65 percent for all BHC banks. We then use these values and calculate the demeaned average capital ratio by county.

Estimation. We estimate the following OLS model with county and time fixed effects, ν_j and τ_y, respectively, for the two years before and after the 2005 hurricane season:

$$\begin{aligned} \mathrm{Y}_{jy} = \nu_j + \tau_y &+ \beta_1(\mathrm{Event}_y \times \mathrm{Affected}_j) \\ &+ \beta_2(\mathrm{Event}_y \times \mathrm{BHCshare}_j) + \beta_3(\mathrm{Event}_y \times \mathrm{Affected}_j \times \mathrm{BHCshare}_j) \\ &+ \beta_4(\mathrm{Event}_t \times \mathrm{CAPaverage}_j) + \beta_5(\mathrm{Event}_y \times \mathrm{Affected}_j \times \mathrm{CAPaverage}_j) \\ &+ \beta_6(\mathrm{Event}_y \times \mathrm{BHCshare}_j \times \mathrm{CAPaverage}_j) \\ &+ \beta_7(\mathrm{Event}_y \times \mathrm{Affected}_j \times \mathrm{BHCshare}_j \times \mathrm{CAPaverage}_j) + \epsilon_{jy}. \end{aligned} \tag{5}$$

$Y_{j,y}$ stands for alternative measures of economic development in county j at year y: the natural logarithms of personal income, number of employed persons, number of unemployed persons, number of persons in the labor force and – not in logs – the unemployment rate. The terms ν_j and τ_y represent county fixed effects and yearly time fixed effects, respectively. $Event_y$ is a dummy variable that is zero for 2003 and 2004 and one for 2006 and 2007. $Affected_j$ is a dummy that categorizes counties as affected and unaffected by the hurricanes. The variables $BHCshare_j$ and $CAPaverage_j$ reflect the demeaned share of BHC banks and banks' risk-based capital ratios per county before the 2005 hurricane season. The term ϵ_{iy} represents the idiosyncratic error term. Standard errors are clustered at the county level.

Results. Regression results are provided in Table 8. First, consider a county with an average share of BHC banks and an average risk-based capitalization of banks (*BHCshare*=0 and *CAPaverage*=0). We find that personal income increases significantly by 5.45 percent in affected counties after the 2005 hurricane season relative to unaffected counties, as reflected in the coefficient of *Event*×*Affected* in Column (1). The next column shows regression results for the log of the number of employed persons as dependent variable. The coefficient of *Event*×*Affected* is positive, but not significant. Column (3) shows that the number of unemployed persons decreases significantly by 10.1 percent. The effect on the labor force, as shown in Column (4), is insignificant. Finally, Column (5) shows that the unemployment rate decreases significantly by 0.45 percentage points in the average affected county after the 2005 hurricane season relative to the control group. Overall, we observe a positive effect of the 2005 hurricane season on economic activity. This presumably reflects reconstruction activities and transfer payments to affected regions.

Next, consider the role of banking structure, *BHCshare*, conditional on an average capitalization of banks (CAPaverage=0), as reflected in the coefficient of the triple interaction term *Event*×*Affected*×*BHCshare*. Results in Column (1) show that a relatively lower share of BHC banks (higher share of independent banks) is beneficial for total personal income in affected counties after the 2005 hurricane season. For example, a 10 percentage points lower share of BHC banks is associated with a 1 percentage point higher increase in total personal income in affected counties following the 2005 hurricane season (0.10×0.1002). The coefficients of *Event*×*Affected*×*BHCshare* are not significant in the regressions in Column (2) to Column (5), where labor market variables are used as dependent variables.

Further, consider the role of average bank capitalization before the 2005 hurricane season, *CAPaverage*, conditional on an average share of BHC banks (*BHCshare*=0), as reflected in the coefficient of the triple interaction term *Event*×*Affected*×CAPaverage. We find a significant positive effect on personal income (Column (1)), the number of employed persons (Column (2)), and the number of persons in the labor force (Column (3)). For example, a 1 percentage point relatively higher average bank capitalization ratio in an affected county is associated with a 0.45 percentage point higher total personal income (0.01×0.4493), a 0.59 percentage point higher number of employed persons (0.01×0.5990), and a 0.58 percentage point higher labor force (0.01× 0.5844) after the 2005 hurricane season relative to the "average" affected county with *CAPaverage*=0.

Finally, we turn to the bottom of Table 8, where difference-in-difference effects for four groups of counties are calculated, based on the 25th and 75th percentiles of *BHCshare* and *CAPaverage*. In line with the previous results, we find the strongest and most consistent positive effects on local economic conditions for affected counties that host a relatively large share of independent banks (25th percentile of *BHCshare*) and a relatively large share of well-capitalized banks (75th percentile of *CAPaverage*). In particular, total personal income and the number of employed persons increase by 7.0 and 3.2 percentage points, respectively, in the aftermath of the 2005 hurricane season relative to unaffected counties. In comparison, affected counties that host only BHC banks (75th percentile of *BHCshare*) and a relatively low share of well-capitalized banks (25th percentile of *CAPaverage*) show no significant increases in total personal income or the number of employed persons relative to unaffected counties (coefficients are 0.0192 and -0.0119, respectively). To the degree that these differences are caused by differences in the structures of the banking systems, policy measures that strengthen (typically more locally focused) independent banks as well as banks' capital buffers would have very significant positive economic effects in the aftermath of a crisis.

Note that the decrease in the number of unemployed persons and the unemployment rate is even stronger for counties that host a relatively large share of BHC banks (see the bottom rows of Table 8). However, in the case of relatively high average capital ratios (75th/ 25th percentiles), these results are not associated with an increase in total personal income or in the number of employed persons. This points to migration effects. In the case of relatively high average capital ratios (75th/ 75th percentiles), the effects on total personal income and the number of employed persons are also significant, but the increases are comparatively smaller than in counties that host a relatively large share of independent banks with relatively high capital ratios (25th/ 75th percentiles).

[Table 8]

Marginal effects of Event×Affected are illustrated in Figure 6. The left panel shows that affected counties perform better after the 2005 hurricane season if they hosted a relatively small share of BHC banks (relatively large share of independent banks). The right figure shows that affected counties with banks that had on average higher risk-based capital ratios before 2005 perform significantly better as well.

[Figure 6]

To sum up, our evidence supports the view that local (independent) banks as well as relatively high bank capital contribute to economic development in the aftermath of a crisis.

5 Conclusions

In this paper we explore how banks react to catastrophic events and the role of banking structure for local economic developments, using Hurricane Katrina and two contemporary hurricanes in 2005 as a natural experiment that exposed banks' borrowers to enormous losses and economic stress. The natural experiment allows us to provide evidence on a *causal effect* of a crisis on banks' business decisions, which is otherwise difficult to identify because of mutual influences and feedback effects.

We find that independent banks based in the disaster areas increase their risk-based capital ratios after the hurricanes, while those that are part of a bank holding company on average do not. Affected independent banks thereby strengthen their buffer against future income shocks and mitigate bankruptcy risks. The effect on independent banks is driven by the subgroup of relatively high-capitalized banks. Independent and relatively low-capitalized banks do not show any significant increases of their risk-based capital ratios following the 2005 hurricane season. This demonstrates that the behavior of banks cannot be generalized for all banks but depends on bank characteristics. Apparently, affected independent banks with a relatively cautious business model (reflected in relatively high risk-based capital ratios before Hurricane Katrina) also behave cautiously after the disaster by increasing their risk-based capital ratios. Independent banks with relatively low risk-based capital ratios, which may be more risky and cause more worries for banking supervisors, are not capable or not willing to build higher capital buffers against potential future losses.

Increases in risk-based capital ratios of independent and high-capitalized banks are associated with decreases in risk-weighted assets. In particular, these banks increase their exposures to U.S. government securities and decrease their loan exposures to non-financial firms. Interestingly, these banks also increase new lending to non-financial firms, as reflected in our evidence on banks' lending under the *Small Business Administration* loan program. This suggests that they do not decrease their exposures to non-financial firms through reduced lending, but through other strategies such as loan sales or securitization.

Finally, we find that the structure of the local banking system plays a role in the economic development after the disaster. Affected counties with a relatively large share of independent and high-capitalized banks exhibit a higher growth of total personal income and employment than affected counties with banks that are predominantly part of a bank holding company or affected counties with relatively low-capitalized banks. These findings thus have important policy implications by highlighting the importance of (more locally focused) independent banks as well as bank capital in facilitating economic development.

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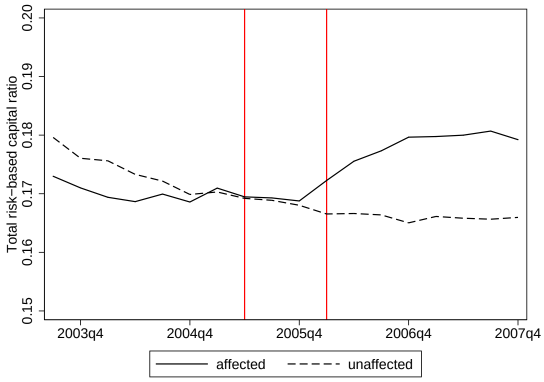
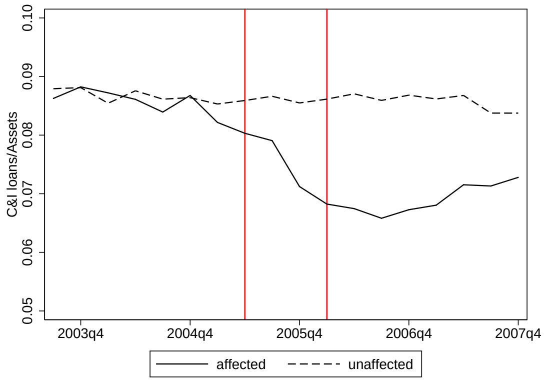
Appendix A: Figures

Figure 1: Impact of the 2005 hurricanes on banks' risk-based capital ratios and loans



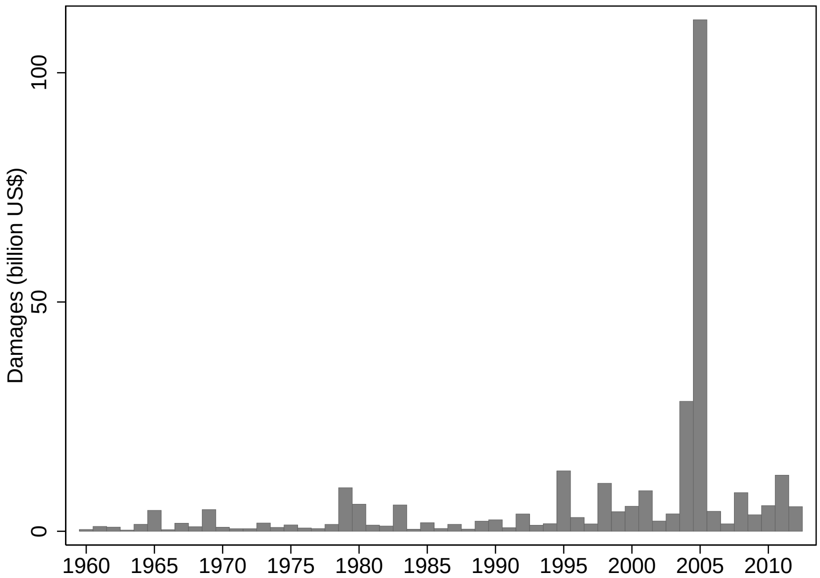
(a) Risk-based capital ratios



(b) C&I loans/ assets

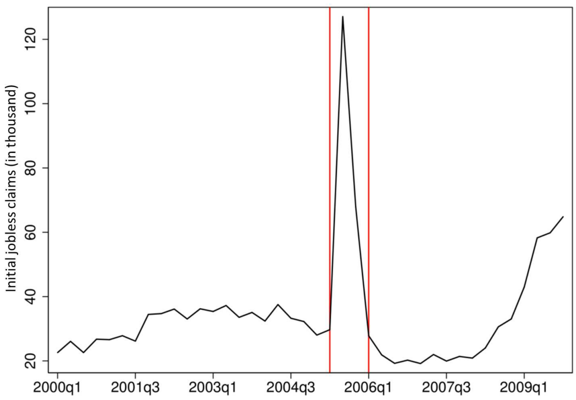
The graphs show the development of banks' risk-based capital ratios and the ratio of the volume of commercial and industrial loans to assets (C&I loans/Assets) from the third quarter of 2003 through the fourth quarter of 2007. The mean values for independent banks located in areas affected by the 2005 hurricanes are represented by a solid line. The mean values for independent banks located in the U.S. Gulf Coast region or neighboring states but not affected by the hurricanes are represented by a dotted line. The solid vertical lines indicate the quarters around the disaster period of the third and fourth quarters of 2005, when Hurricanes Katrina, Rita and Wilma hit the U.S. Gulf Coast region.

Figure 2: Annual disaster losses since 1960

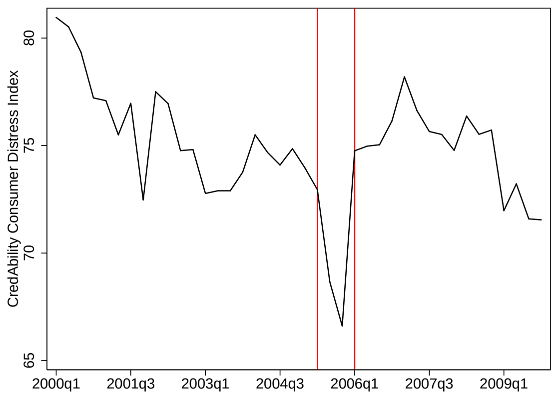


The figure shows the total sum of yearly disasters losses for the states in our baseline sample: Alabama, Louisiana, Florida, Mississippi, Georgia, Tennessee, Oklahoma and Arkansas. The numbers are expressed in $billion and adjusted to 2011 dollar values. The data source is the Hazards & Vulnerability Research Institute (Sheldus database).

Figure 3: Impact of Hurricane Katrina on the Louisiana economy



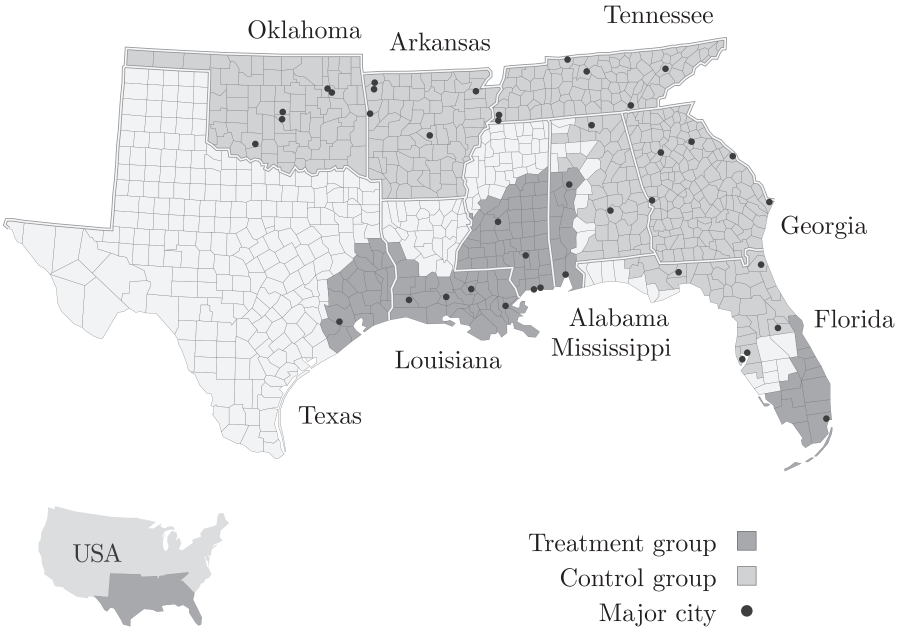
(a) Initial jobless claims



(b) CredAbility Consumer Distress Index

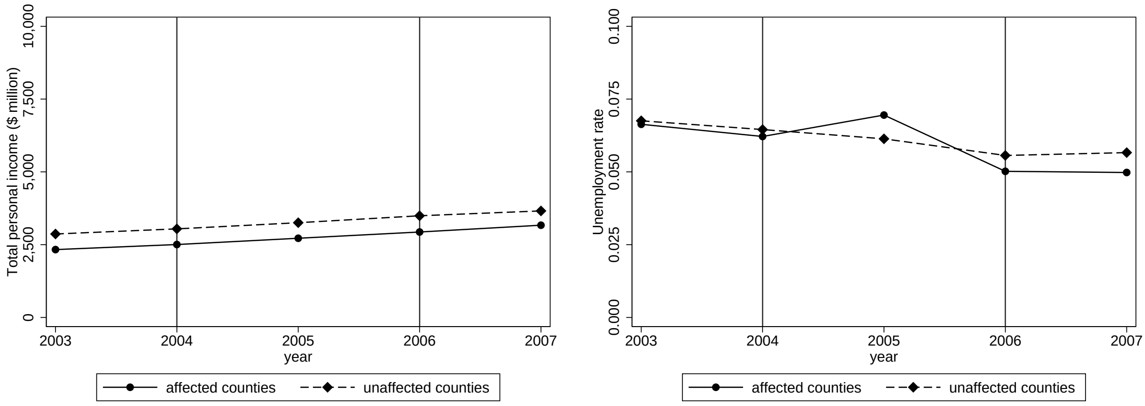
The left graph shows initial jobless claims (in thousand) and the right graph shows the CredAbility Consumer Distress Index for Louisiana, where a higher score shows a more favorable situation and a score under 70 indicates financial distress. Both graphs reflect quarterly values from the first quarter of 2000 through the fourth quarter of 2009. The solid vertical lines indicate the quarters around the disaster period of the third and fourth quarters of 2005, when Hurricanes Katrina, Rita and Wilma hit the U.S. Gulf Coast region. The data source for both graphs is the FRED database of the St. Louis Fed.

Figure 4: 2005 hurricane disaster areas



This figure shows counties in the U.S. Gulf Coast region and neighboring states that were affected by the 2005 hurricane season (Katrina, Rita and Wilma). The dark-grey shaded area comprises counties that were eligible for individual and public disaster assistance, which we classify as affected counties. Banks with headquarters in these counties are classified as affected banks. The light-grey shaded area comprises counties that did not receive disaster assistance, which we classify as unaffected counties. Banks with headquarters in these counties are classified as unaffected banks. The white shaded area includes counties that were eligible only for public disaster assistance, which we exclude from the sample. Banks with headquarters in these counties are also excluded from the sample.

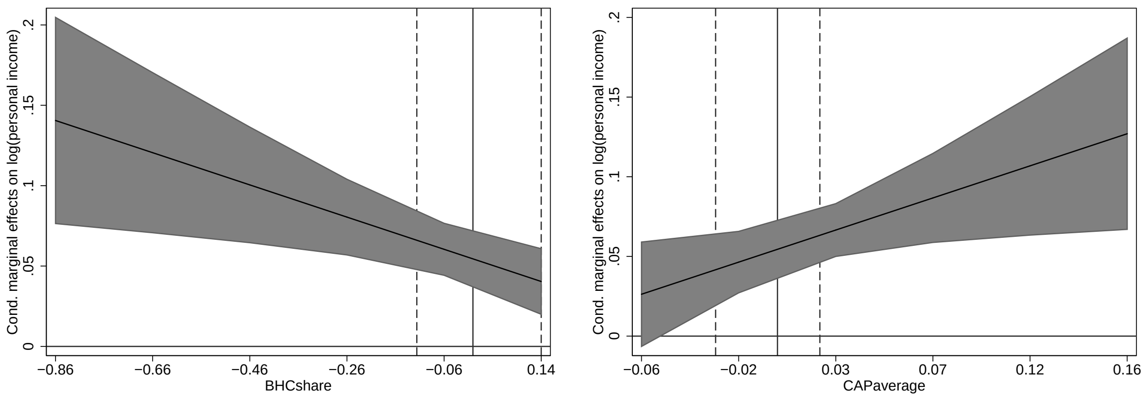
Figure 5: Economic developments in affected and unaffected counties



(a) Total personal income (b) Unemployment rate

This figure illustrates economic developments in counties affected (solid lines) and unaffected (dashed lines) by the hurricane season of 2005. The left graph shows counties' average log of personal income, and the right graph shows counties' average unemployment rates.

Figure 6: Structure of the local banking system and economic development



(a) BHCshare (demeaned) (b) CAPaverage (demeaned)

This figure illustrates marginal effects of Event×Affected on the log of total personal income on county-level, conditional on the average share of BHC banks (left panel) and the average risk-based capital ratio (right panel) in affected counties. These effects correspond to regression results in Column (1) of Table 8. Note that BHCshare and CAPaverage are demeaned. Original values for BHCshare range from 0 to 1 with a mean of 0.86. Original values for CAPaverage range from 0.10 to 0.31 with a mean of 0.15. Values on the x-axis range from the min to the max of the respective variable. The solid vertical lines represent the means, i.e., zero, and the dashed lines represent the 25th and 75th percentiles of these variables.

Appendix B: Tables

Table 1: Variable description

Notes: The source for all variables as well as their descriptions is the FDIC, if not stated otherwise. For more details, refer to https://www.fdic.gov/bank/statistical/.

Variable name	FDIC code	Description
Bank level variables		
Assets	asset	**Total assets.** The sum of all assets owned by the institution including cash, loans, securities, bank premises and other assets.
Bank size	log(numemp)	**Bank size.** The natural logarithm of the number of full-time employees on the payroll of the bank and its subsidiaries.
BHC	namehcr	**Bank Holding Company bank.** Dummy variable that we assign a value of zero if "namehcr" is blank and a value of one otherwise.
C&I loans	lnci	**Commercial and industrial loans.** All loans excluding loans secured by real estate, loans to individuals, loans to depository institutions and foreign governments, loans to states and political subdivisions and lease financing receivables.
CON loans	lncon	**Consumer loans.** Loans to individuals for household, family, and other personal expenditures including outstanding credit-card balances and other secured and unsecured consumer loans.
Credit demand		**Credit demand.** Sum of accepted and denied loans on the bank-quarter level. Source: Home Mortgage Disclosure Act (HMDA) database.
GOV	scus	**Government securities.** Total U.S. Treasury securities plus U.S. Government agency and corporation obligations.
NPL	p9asset	**Non-performing loans.** Total assets past due 90 or more days and still accruing interest.
preCAP		**(Pre-Hurricane Katrina) capital ratio.** A dummy variable which is zero if a bank's average risk-based capital ratio during the eight quarters before the event is below the sample median (preCap=0) and one otherwise (preCAP=1). Source: Own calculations based on FDIC data.
RE loans	lnre	**Real-estate loans.** Loans secured primarily by real estate, whether originated by the bank or purchased.
RECO loans	lnrenres	**Commercial real-estate loans.** Nonresidential loans primarily secured by real estate.
RECON loans	lnrecons	**Construction and development loans.** Construction and land development loans secured by real estate held in domestic offices. This item includes loans for all property types under construction, as well as loans for land acquisition and development.
Risk-based capital ratio	rbcrwaj	**Risk-based capital ratio.** Tier 1 capital and Tier 2 capital divided by the bank's risk-weighted assets. For some banks, the nominator also includes Tier 3 capital allocated for market risk, net of all deductions. For details, see "Schedule RC-R – Regulatory Capital" of the FDIC.
RoA	roaptx	**Return over assets.** Net income after taxes and extraordinary items (annualized) to average total assets.
RWA	rwaj	**Risk-weighted assets.** Assets adjusted for risk-based capital definitions that comprise on-balance-sheet as well as off-balance-sheet items multiplied by risk weights that range from 0 to 100% (under Basel I).
Total capital	rbct1j+rbct2	**Total capital.** The sum of Tier 1 capital and Tier 2 capital.
Small business loans		**SBA loans.** The amount of loans to small business. Source: U.S. Small Business Administration.
Z-score		**Z-score.** We calculate the z-score for each bank and quarter as the natural logarithm of the sum of a bank's return on assets (roaptx) and its core capital ratio (eqv), standardized by the standard deviation (12 quarter rolling) of the bank's return on assets. Source: Own calculations based on FDIC data.
County level variables		
BHCshare		**Share of BHC banks.** The share of banks belonging to a bank holding company per county, based on all banks with a branch in a certain county before the 2005 hurricane season (June 2005). Banks' sum of deposits per county are used as weighs. Source: Own calculations based on Summary of Deposits database of the FDIC.
CAPaverage		**Average bank capitalization.** The average of banks' risk-based capital ratios per county, based on all banks with a branch in a certain county before the 2005 hurricane season (June 2005). Banks' sum of deposits per county are used as weighs. Source: Own calculations based on Summary of Deposits database of the FDIC.
Employed		**Employed persons.** The number of employed persons per county and year. Source: Bureau of Labor Economics.
Labor force		**Persons in labor force.** The number of all employed an unemployed persons per county and year. Source: Bureau of Labor Economics.
Personal income		**(Total) personal income.** The income received by, or on behalf of all persons resident in a county per year. It includes wages and salaries, supplements to wages and salaries, proprietors' income, dividends, interest, and rent, and personal current transfer receipts, less contributions for government social insurance. Source: Bureau of Economic Analysis.
Unemployed		**Unemployed persons.** The number of unemployed persons per county and year. Source: Bureau of Labor Economics.
UR		**Unemployment rate.** The percentage of the labor force that is unemployed per county and year. Source: Bureau of Labor Economics.

Table 2: Descriptive statistics

This table reports descriptive statistics for all variables over the period two years before the hurricane event in 2005. The upper panel shows mean values and standard deviations for independent banks (i.e., banks that do not belong to a BHC) that reside in counties that were affected by the hurricane (affected) and banks operating in counties unaffected by the event (unaffected) in the top panel. The sample inlcudes banks in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma. Descriptive statistics for SBA loans (denoted by *) refer to the sample used in Section 4.5, which includes 73 affected and 264 unaffected independent and BHC banks. The bottom panel provides descriptive statistics for the analysis on county level.
The last two columns show the normalized differences (Norm. Diff.) according to Imbens and Wooldridge (2009) and compare differences between banks/ counties that were affected versus banks/ counties that were not affected ((1) vs (2)). As a rule of thumb, groups are regarded as sufficiently equal and adequate for linear regression methods if normalized differences are largely in the range of ± 0.25. A detailed description of all variables is given in Table 1.

	(1) affected		(2) unaffected		Norm. Diff.
Bank sample	Mean	SD	Mean	SD	(1) vs (2)
Assets ($ million)	424.4568	1122.7046	244.8142	836.5487	0.1283
Bank size	3.8657	1.0052	3.5775	0.8791	0.2158
C&I loans/Assets	0.0851	0.0775	0.0866	0.0642	-0.0146
CON loans/Assets	0.0483	0.0485	0.0732	0.0603	-0.3207
Gov. securities/Assets	0.1747	0.1408	0.1703	0.1385	0.0222
Loans/Assets	0.6466	0.1713	0.6706	0.1543	-0.1042
NPL/Assets	0.0013	0.0029	0.0016	0.0030	-0.0657
RE loans/Assets	0.5010	0.2058	0.4861	0.1860	0.0536
RECO loans/Assets	0.1671	0.1284	0.1486	0.1123	0.1082
RECONS loans/Assets	0.0663	0.0639	0.0708	0.0788	-0.0445
Risk based capital ratio	0.1701	0.0576	0.1733	0.0630	-0.0368
Risk-weighted assets/Assets	0.6426	0.1214	0.6830	0.1208	-0.2356
RoA	0.0094	0.0094	0.0097	0.0096	-0.0207
SBA loans ($000)*	1608.8426	2890.6289	1741.0798	5049.5701	-0.0227
SBA loans net of guarantees ($000)*	402.8130	721.2119	455.4962	1338.1543	-0.0347
Tier capital/Assets	0.1053	0.0276	0.1136	0.0306	-0.2027
Z-score	3.6972	0.8996	3.7628	0.8841	-0.0520
Credit demand	9.7183	1.9764	9.5051	1.6228	0.0834
Unemployment rate	0.0563	0.0123	0.0542	0.0146	0.1070
Number of banks	94		164		
Number of observations	752		1312		

	(1) affected		(2) unaffected		Norm. Diff.
County sample	Mean	SD	Mean	SD	(1) vs (2)
BHCshare (before demeaning)	0.8495	0.2241	0.8693	0.2197	-0.0631
CAPaverage (before demeaning)	0.1533	0.0391	0.1513	0.0376	0.0363
No. of employed persons (000)	43.6428	59.2071	54.9142	136.0716	-0.0760
No. of persons in labor force (000)	46.2746	62.5010	57.8899	143.0961	-0.0744
No. of unemployed persons (000)	2.6317	3.4257	2.9757	7.1244	-0.0435
Personal income ($ million)	2,418.0714	3,340.6302	2,955.3050	7,277.4510	-0.0671
Unemployment rate	0.0643	0.0166	0.0660	0.0198	-0.0691
Number of counties	88		88		
Number of observations	176		176		

Table 3: Baseline results

This table shows results for regressions in which banks' total risk-based capital ratio is the dependent variable. The sample includes quarterly data for all independent banks (not part of a bank holding company) in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Credit demand is the log of a bank's volume of loan applications as reported under the Home Mortgage Disclosure Act. RoA is banks' return over assets. NPL/Assets represents non-performing loans over assets. Bank size is the natural logarithm of banks' number of employees. UR represents the unemployment rate for the county where a bank's headquarters is based. A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year dummies (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.

	Risk-based capital ratio			
	(1)	(2)	(3)	(4)
Event × Affected	0.0104**	0.0149***	0.0124**	0.0131**
	(0.0045)	(0.0051)	(0.0053)	(0.0053)
Affected		-0.0031		
		(0.0075)		
Credit demand			-0.0062***	-0.0052***
			(0.0018)	(0.0017)
RoA				-0.0005
				(0.0027)
NPL/Assets				-0.0036
				(0.2624)
Bank size				-0.0237**
				(0.0093)
UR				0.0724
				(0.1379)
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes
N. of Banks	258	258	182	182
N. of Obs.	3795	3795	2415	2415
Adj. R2	0.8670	0.0037	0.8576	0.8607
Within R2	0.0127	0.0043	0.0399	0.0625

Table 4: The role of bank capitalization

This table shows results for regressions in which banks' total risk-based capital ratio is the dependent variable and the terms Event, Affected and Event×Affected are interacted with a dummy variable which is zero if a bank's average risk-based capital ratio during the eight quarters before the event is below the sample median (preCap=0) and one otherwise (preCAP=1). The sample includes quarterly data for all independent banks (not part of a bank holding company) in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).

Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Credit demand is the log of a bank's volume of loan applications as reported under the Home Mortgage Disclosure Act. RoA is banks' return over assets. NPL/Assets represents non-performing loans over assets. Bank size is the natural logarithm of banks' number of employees. Regional unemployment rate (UR) represents the unemployment rate for the county where a bank's headquarters is based. A detailed description of all variables is given in Table 1.

Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. At the bottom, we present estimates of the difference-in-difference effect of Event×Affected for both realizations of preCAP.

	Risk-based capital ratio			
	(1)	(2)	(3)	(4)
Event × Affected	0.0009	0.0037	0.0059	0.0069
	(0.0057)	(0.0059)	(0.0060)	(0.0056)
Event × Affected × preCAP	0.0178**	0.0132	0.0142	0.0131
	(0.0085)	(0.0090)	(0.0107)	(0.0102)
preCAP		0.0913***		
		(0.0062)		
Affected		0.0040		
		(0.0027)		
Affected × preCAP		-0.0055		
		(0.0099)		
Event × preCAP	-0.0269***	-0.0260***	-0.0201***	-0.0222***
	(0.0046)	(0.0047)	(0.0055)	(0.0051)
Credit demand			-0.0064***	-0.0052***
			(0.0017)	(0.0016)
RoA				-0.0004
				(0.0026)
NPL/Assets				-0.0059
				(0.2055)
Bank size				-0.0283***
				(0.0091)
UR				0.0325
				(0.1329)
Bank FE	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of Banks	258	258	182	182
N. of Obs.	3795	3795	2415	2415
Adj. R2	0.8757	0.4484	0.8622	0.8665
Within R2	0.0777	0.4493	0.0718	0.1025
Difference-in-difference effects for relatively low (preCAP=0) or high (preCAP=1) capitalized banks				
Event×Affected for preCAP=0	0.0009	0.0037	0.0059	0.0069
	(0.0057)	(0.0059)	(0.0060)	(0.0056)
Event×Affected for preCAP=1	0.0187***	0.0169**	0.0201**	0.0200**
	(0.0063)	(0.0069)	(0.0089)	(0.0087)

Table 5: The role of internal capital markets

This table shows results for regressions in which banks' total risk-based capital ratio is the dependent variable and the terms Event, Affected and Event×Affected are interacted with a dummy variable that indicates independent banks ($BHC = 0$) or banks that belong to a bank holding company ($BHC = 1$). The sample includes quarterly data for all banks in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Credit demand is the log of a bank's volume of loan applications as reported under the Home Mortgage Disclosure Act. RoA is banks' return over assets. NPL/Assets represents non-performing loans over assets. Bank size is the natural logarithm of banks' number of employees. UR represents the unemployment rate for the county where a bank's headquarters is based. A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively. At the bottom, we present estimates of the difference-in-difference effect of Event×Affected for independent banks (BHC=0) and for banks that belong to a bank holding company (BHC=1).

	Risk-based capital ratio			
	(1)	(2)	(3)	(4)
Event × Affected	0.0104**	0.0149***	0.0126**	0.0130**
	(0.0044)	(0.0051)	(0.0054)	(0.0054)
Event × Affected × BHC	-0.0089*	-0.0133**	-0.0098*	-0.0101*
	(0.0048)	(0.0055)	(0.0059)	(0.0058)
Affected		-0.0031		
		(0.0075)		
BHC		-0.0201***		
		(0.0051)		
Affected × BHC		0.0076		
		(0.0084)		
Event × BHC	0.0043	0.0030	0.0032	0.0034
	(0.0027)	(0.0029)	(0.0030)	(0.0029)
Credit demand			-0.0012	-0.0005
			(0.0008)	(0.0008)
RoA				0.0006
				(0.0012)
NPL/Assets				-0.0510
				(0.1219)
Bank size				-0.0129***
				(0.0040)
UR				0.0548
				(0.0409)
Bank FE	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of Banks	1253	1253	859	859
N. of Obs.	19288	19288	11971	11971
Adj. R2	0.8883	0.0233	0.8840	0.8855
Within R2	0.0042	0.0222	0.0099	0.0223
Difference-in-difference effect for independent banks (BHC=0) and BHC banks (BHC=1)				
Event×Affected for BHC=0	0.0104**	0.0149***	0.0126**	0.0130**
	(0.0044)	(0.0051)	(0.0054)	(0.0054)
Event×Affected for BHC=1	0.0014	0.0016	0.0028	0.0029
	(0.0019)	(0.0020)	(0.0022)	(0.0021)

Table 6: Balance sheet exposures

This table shows results for regressions in which banks' balance sheet exposures serve as dependent variables: total risk-based capital ratio and – all expressed as natural logarithms – total capital; risk-weighted assets; government securities; real estate loans; commercial real estate loans; construction and development loans; consumer loans; commercial and industrial loans. The sample includes quarterly data for all banks in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. The terms Event, Affected and Event×Affected are interacted with two variables: a dummy variable that indicates independent banks (BHC=0) or banks that belong to a bank holding company (BHC=1) and a dummy variable which zero if a bank's average risk-based capital ratio during the eight quarters before the event is below the sample median (preCap=0) and one otherwise (preCAP=1). A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.
At the bottom, we present estimates of the difference-in-difference effect of Event×Affected for the combination of independent banks (BHC=0) with low and high capital ratios (CAP=0 or CAP=1) and for banks that belong to a bank holding company (BHC=1) with low and high capital ratios (CAP=0 or CAP=1).

Dependent variable:	RBCR (1)	log(capital) (2)	log(RWA) (3)	log(GOV) (4)	log(RE loans) (5)	log(RECO loans) (6)	log(RECON loans) (7)	log(CON loans) (8)	log(C&I loans) (9)
Event × Affected	0.0009	0.0149	0.0172	-0.3302	0.0289	0.0885	0.3102	-0.1020	0.0560
	(0.0057)	(0.0512)	(0.0592)	(0.2265)	(0.0658)	(0.0862)	(0.2940)	(0.1168)	(0.1282)
Event × BHC	-0.0041	0.0121	0.0386	-0.3713*	0.0763**	-0.0230	0.3638***	-0.0965	-0.0847
	(0.0027)	(0.0316)	(0.0327)	(0.2117)	(0.0337)	(0.0441)	(0.0984)	(0.0596)	(0.0585)
Event × Affected × BHC	0.0030	0.0274	-0.0070	0.5433**	-0.0201	-0.1048	-0.4030	0.1300	-0.0838
	(0.0060)	(0.0585)	(0.0660)	(0.2505)	(0.0737)	(0.0941)	(0.3084)	(0.1244)	(0.1367)
Event×preCAP	-0.0269***	-0.1862***	-0.0402	-0.5632***	0.0072	0.1341*	0.3283*	-0.0166	-0.0184
	(0.0046)	(0.0375)	(0.0424)	(0.2136)	(0.0441)	(0.0699)	(0.1742)	(0.0687)	(0.0849)
Event × Affected × preCAP	0.0178**	-0.0096	-0.1017	0.7552**	-0.0706	-0.1576	-0.5840	0.0045	-0.2247
	(0.0085)	(0.0621)	(0.0745)	(0.3058)	(0.0889)	(0.1283)	(0.3607)	(0.1426)	(0.1621)
Event × BHC × preCAP	0.0152***	-0.0219	-0.1001**	0.4517**	-0.1408***	-0.1802**	-0.3821**	0.0249	-0.0210
	(0.0049)	(0.0408)	(0.0460)	(0.2200)	(0.0484)	(0.0757)	(0.1911)	(0.0740)	(0.0894)
Event×Affected×BHC×preCAP	-0.0206**	-0.0162	0.1034	-0.9100***	0.0775	0.1648	0.5770	-0.1153	0.2673
	(0.0092)	(0.0707)	(0.0832)	(0.3268)	(0.0987)	(0.1389)	(0.3862)	(0.1575)	(0.1734)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Banks	1253	1253	1253	1253	1253	1253	1253	1253	1253
N. of Obs.	19288	19288	19288	19288	19288	19288	19288	19288	19288
Adj. R2	0.8933	0.9812	0.9808	0.8736	0.9801	0.9637	0.8930	0.9406	0.9502
Within R2	0.0493	0.1284	0.0457	0.0126	0.0286	0.0110	0.0035	0.0049	0.0067
Difference-in-difference effect for subgroups of banks									
Event×Aff. for BHC=0, preCAP=0	0.0009	0.0149	0.0172	-0.3302	0.0289	0.0885	0.3102	-0.1020	0.0560
	(0.0057)	(0.0512)	(0.0592)	(0.2265)	(0.0658)	(0.0862)	(0.2940)	(0.1168)	(0.1282)
Event×Aff. for BHC=0, preCAP=1	0.0187***	0.0053	-0.0845*	0.4251**	-0.0416	-0.0691	-0.2738	-0.0976	-0.1687*
	(0.0063)	(0.0351)	(0.0453)	(0.2057)	(0.0597)	(0.0950)	(0.2088)	(0.0818)	(0.0991)
Event×Aff. for BHC=1, preCAP=0	0.0039**	0.0423	0.0102	0.2132**	0.0089	-0.0163	-0.0928	0.0280	-0.0278
	(0.0018)	(0.0283)	(0.0292)	(0.1070)	(0.0332)	(0.0378)	(0.0933)	(0.0428)	(0.0474)
Event×Aff. for BHC=1, preCAP=1	0.0011	0.0165	0.0119	0.0584	0.0158	-0.0091	-0.0999	-0.0828	0.0147
	(0.0030)	(0.0188)	(0.0229)	(0.0427)	(0.0273)	(0.0377)	(0.1018)	(0.0512)	(0.0397)

Table 7: Lending activities (SBA loans)

This table shows results for regressions in which a bank's amount of SBA loans serves as dependent variables. In the first three columns we use the amount of total SBA loans (expressed as natural logarithms). In the last three columns we use the amount of SBA loans net of guarantees (expressed as natural logarithms). For each variable we show results for the total amount per bank, the amount lend to borrowers in the banks' core markets (where they own a branch) and the amount lend to borrowers in the banks' non-core markets (where they do not own a branch). The sample includes quarterly data for all banks in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. The terms Event, Affected and Event×Affected are interacted with two variables: a dummy variable that indicates independent banks (BHC=0) or banks that belong to a bank holding company (BHC=1) and a dummy variable which zero if a bank's average risk-based capital ratio during the eight quarters before the event is below the sample median (preCap=0) and one otherwise (preCAP=1). A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.
At the bottom, we present estimates of the difference-in-difference effect of Event×Affected for the combinations of independent banks (BHC=0) with relatively low and high pre-Hurricane Katrina capital ratios (preCAP=0 or preCAP=1) and banks that belong to a bank holding company (BHC=1) with relatively low and high pre-Hurricane Katrina capital ratios (preCAP=0 or preCAP=1).

	log(SBA loans)			log(SBA loans net of guarantees)		
	total	core markets	non-core markets	total	core markets	non-core markets
	(1)	(2)	(3)	(4)	(5)	(6)
Event × Affected	2.0870	-0.1103	2.3074	1.6826	-0.1719	1.9171
	(2.5550)	(2.4659)	(2.0010)	(2.2748)	(2.1885)	(1.7849)
Event × BHC	0.9809	-0.4161	0.8428	0.8271	-0.3584	0.6810
	(1.1212)	(1.0835)	(1.2246)	(0.9931)	(0.9423)	(1.0811)
Event × Affected × BHC	-0.7373	1.1709	-2.6882	-0.5559	1.0298	-2.2844
	(2.7042)	(2.6477)	(2.1754)	(2.4105)	(2.3536)	(1.9414)
Event × preCAP	-2.6019	-1.8358	-0.6256	-2.3282	-1.6041	-0.6174
	(1.6721)	(1.6997)	(1.9058)	(1.5260)	(1.5161)	(1.7002)
Event × Affected × preCAP	2.5299	5.6157	-0.0495	2.5885	5.1589	0.0485
	(3.6816)	(3.6827)	(3.3901)	(3.3535)	(3.3271)	(3.0400)
Event × BHC × preCAP	2.3016	1.8918	0.3937	2.0926	1.6240	0.4615
	(1.7840)	(1.8130)	(1.9916)	(1.6243)	(1.6156)	(1.7775)
Event × Affected × BHC × preCAP	-4.4513	-6.7012*	-0.0018	-4.2878	-6.0704*	-0.1384
	(3.9003)	(3.9313)	(3.5986)	(3.5424)	(3.5404)	(3.2238)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of Banks	337	337	337	337	337	337
N. of Obs.	1341	1341	1341	1341	1341	1341
Adj. R2	0.4252	0.4369	0.5605	0.4445	0.4542	0.5722
Within R2	0.0096	0.0060	0.0033	0.0094	0.0062	0.0032
Difference-in-difference effects for subgroups of banks						
Event×Affected for BHC=0, preCAP=0	2.0870	-0.1103	2.3074	1.6826	-0.1719	1.9171
	(0.4148)	(0.9644)	(0.2499)	(0.4602)	(0.9375)	(0.2837)
Event×Affected for BHC=0, preCAP=1	4.6169*	5.5054**	2.2579	4.2711*	4.9870**	1.9655
	(0.0826)	(0.0450)	(0.4101)	(0.0840)	(0.0475)	(0.4252)
Event×Affected for BHC=1, preCAP=0	1.3497	1.0606	-0.3808	1.1267	0.8579	-0.3674
	(0.1291)	(0.2725)	(0.6552)	(0.1591)	(0.3230)	(0.6303)
Event×Affected for BHC=1, preCAP=1	-0.5717	-0.0249	-0.4321	-0.5726	-0.0536	-0.4573
	(0.5410)	(0.9798)	(0.6125)	(0.4836)	(0.9495)	(0.5436)

Table 8: Effects on growth and employment

This table shows regressions results of Eq. (5) with alternative dependent variables that measure economic activity on county-level: log of total personal income; log of number of employed persons; log of number of unemployed persons; log of persons in the labor force; unemployment rate (UR). The sample includes yearly data for all counties in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period $\pm$ 2 years around the 2005 hurricane season (2003 to 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates affected counties (Affected=1) from unaffected counties (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. The terms Event, Affected and Event×Affected are interacted with two continuous variables: one variable that indicates the share of banks that belong to a bank holding company per county (BHCshare) and one that indicates banks' average risk-based capital ratio per county (CAPaverage). A detailed description of all variables is given in Table 1.
County fixed effects (County FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on county level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.
At the bottom, we present estimates of the difference-in-difference effect of Event×Affected for alternative combination of the 25th and 75th percentiles of the share of banks that belong to a bank holding company (BHCshare) and banks' average risk-based capital ratio (CAPaverage).

	log(personal income) (1)	log(# employed) (2)	log(# unemployed) (3)	log(# labor force) (4)	UR (5)
Event × Affected	0.0545***	0.0134	-0.1014***	0.0087	-0.0045**
	(0.0098)	(0.0098)	(0.0339)	(0.0099)	(0.0019)
Event × BHCshare	0.0344	0.0188	0.0317	0.0179	-0.0007
	(0.0279)	(0.0210)	(0.0846)	(0.0200)	(0.0053)
Event × Affected × BHCshare	-0.1002**	-0.0589	-0.1631	-0.0664	-0.0070
	(0.0454)	(0.0448)	(0.1982)	(0.0475)	(0.0107)
Event × CAPaverage	-0.7880***	-0.6560***	-1.2509**	-0.7278***	-0.0647*
	(0.1366)	(0.1401)	(0.5619)	(0.1323)	(0.0376)
Event × Affected × CAPaverage	0.4493*	0.5990**	0.2895	0.5844**	-0.0149
	(0.2355)	(0.2544)	(0.7933)	(0.2524)	(0.0447)
Event × BHCshare × CAPaverage	-1.4290**	-0.6531	-3.5332	-0.8180*	-0.1520
	(0.6466)	(0.5221)	(2.5921)	(0.4908)	(0.1679)
Event × Affected × BHCshare × CAPaverage	2.0841**	-0.0134	2.6334	0.1324	0.1336
	(1.0386)	(1.1763)	(4.0736)	(1.2037)	(0.2190)
County FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
N. of Counties	176	176	176	176	176
N. of Obs.	704	704	704	704	704
Adj. R2	0.9990	0.9990	0.9800	0.9990	0.7117
Within R2	0.2191	0.0849	0.0588	0.0977	0.0510
Difference-in-difference effects for different percentiles of BHCshare and CAPaverage, respectively					
Event×Affected for 25th and 25th percentiles	0.0601***	0.0030	-0.0822	0.0002	-0.0028
	(0.0139)	(0.0149)	(0.0519)	(0.0153)	(0.0027)
Event×Affected for 25th and 75th percentiles	0.0701***	0.0319***	-0.0829*	0.0276***	-0.0042*
	(0.0105)	(0.0100)	(0.0461)	(0.0104)	(0.0026)
Event×Affected for 75th and 25th percentiles	0.0192	-0.0119	-0.1432***	-0.0178	-0.0056*
	(0.0175)	(0.0194)	(0.0547)	(0.0195)	(0.0029)
Event×Affected for 75th and 75th percentiles	0.0549***	0.0168*	-0.1115***	0.0112	-0.0054**
	(0.0115)	(0.0101)	(0.0409)	(0.0100)	(0.0025)

Appendix C: Short-term effects on bank asset quality

In this section, we provide further empirical evidence that Hurricane Katrina, Rita and Wilma had an adverse effect on banks' asset quality by exploring bank profitability and bank risk in Q3 and Q4 2005. In particular, we expect lower bank profitability and higher bank risk.

Estimation. Formally, we estimate the following equation:

$$\mathrm{Y}_{it} = \nu_i + \tau_\gamma + \beta_1(\mathrm{EventST}_t \times \mathrm{Affected}_i) + \epsilon_{it}. \tag{6}$$

The dependent variable Y_{it} stands for return on assets (RoA) or z-score of bank i at quarter t, which reflects bank profitability and bank stability, respectively.[30] The variables ν_i and τ_γ represents bank and quarter fixed effects, respectively. The variable $EventST_t$ is a short-term time dummy with a value of zero for the two quarters before the hurricanes (Q1 and Q2 2005) and a value of one for the two quarters when the hurricanes occurred (Q3 and Q4 2005). The variable $Affected_i$ is a dummy variable of bank i that is one if the bank is located in a county classified by FEMA as eligible for "public and private disaster assistance" and thus belongs to the treatment group, and zero otherwise (for the control group). Hence, the interaction term $EventST_t \times Affected_i$ is one if both the variable $EventST_t$ and the variable *Affectedi* amount to one, and zero otherwise. The corresponding coefficient β_1 is the main interest. It captures the average effect of the hurricanes on the RoA or z-score of affected banks relative to the control group. Note that the single term $Affected_i$ and the single term $EventST_t$ are not directly included in the equation because they are fully captured by the bank and quarter fixed effects, respectively. Finally, ϵ_{it} is the idiosyncratic error term. To account for heterogeneity among banks, we use clustered standard errors at the bank level.

[30] The z-score is defined as the natural logarithm of the sum of a bank's RoA and its core capital over assets, standardized by the standard deviation of the bank's RoA. A lower z-score indicates lower bank stability.

Results. First, as shown in Column 1 of Table A.1, we estimate the effect of Hurricanes Katrina, Rita and Wilma on banks' RoA. We observe that profits decline significantly for banks that were affected by the hurricanes relative to banks that were not affected. The effect of 0.0009 represents about 10% of banks' average RoA of 0.01. The true effect on banks may be even larger because banks tend to underreport losses in times of crisis (Gunther and Moore, 2003). Regression results for banks' z-scores are presented in Column 2. The results show that affected banks became significantly more risky during the two quarters when the hurricanes met the U.S. Gulf Coast relative to unaffected banks. The coefficient of -0.1099 means that the ratio (RoA+Capital)/SD(RoA), where RoA is return on assets, Capital is core capital over assets and SD(RoA) is the standard deviation of RoA, decreases by about 10.99 percent for affected banks relative to unaffected banks following the 2005 hurricane season, which is economically highly relevant.

Summing up, the regression results provide evidence that the 2005 hurricane season had an adverse effect on bank's asset quality, as reflected in lower bank profitability and higher bank risk.

Table A.1: Evidence on short-term effects

This table shows results for regressions of Equation (6) in which banks' return on assets (RoA) and banks' z-scores are the dependent variables. The sample includes quarterly data for all independent banks (not part of a bank holding company) in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the four quarters of 2005.
EventST is a dummy variable that is zero for the first two quarters of 2005 and one for the last two quarters of 2005 (when the hurricanes occured). Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Bank fixed effects (Bank FE) and quarterly dummies (Time FE) are included in each regression. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.

	RoA (1)	Z-score (2)
EventST × Affected	-0.0009**	-0.1099***
	(0.0004)	(0.0420)
Time FE	Yes	Yes
Bank FE	Yes	Yes
N. of Banks	258	258
N. of Obs.	1023	1017
Within R2	0.0178	0.0481

Online Appendix

This appendix is for online publication only and provides further robustness regressions for the paper "How do banks react to catastrophic events? Evidence from Hurricane Katrina".

Table O-1: Robustness - alternative regional samples

This table shows results for regressions in which banks' total risk-based capital ratio is the dependent variable. The sample includes quarterly data for all independent banks (not part of a bank holding company) for different samples: AL& FL represents results for banks in Florida and Alabama only; AL&LA&FL&MS comprises counties in Alabama, Louisiana, Florida and Mississippi; AL&LA&FL&MS&TX comprises counties in Alabama, Louisiana, Florida, Mississippi and Texas; Baseline includes counties in Alabama, Louisiana, Florida, Mississippi, Texas, Georgia, Tennessee, Arkansas and Oklahoma. We observe the samples over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.

	Risk-based capital ratio			
	AL&FL	AL&LA&FL&MS	AL&LA&FL&MS&TX	Baseline
	(1)	(2)	(3)	(4)
Event × Affected	0.0228***	0.0149**	0.0180***	0.0104**
	(0.0073)	(0.0060)	(0.0060)	(0.0045)
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
N. of Banks	83	115	133	258
N. of Obs.	1204	1666	1931	3795
Adj. R2	0.8108	0.8665	0.8558	0.8670
Within R2	0.0629	0.0284	0.0343	0.0127

Table O-2: Robustness – extended control group or treatment group

This table shows results for regressions in which banks' total risk-based capital ratio is the dependent variable, using an extended control group or treatment group. The sample includes quarterly data for all independent banks (not part of a bank holding company) in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007). Compared to the baseline sample, first, we include to the control group all banks with their headquarter in a county that we previously ignored, because these counties were not eligible for individual but only for public disaster assistance (Columns (1) to (4)). Second, we include these banks to the treatment group instead of to the control group (Columns (5) to (8)).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Credit demand is the log of a bank's volume of loan applications as reported under the Home Mortgage Disclosure Act. RoA is banks' return over assets. NPL/Assets represents non-performing loans over assets. Bank size is the natural logarithm of banks' number of employees. UR represents the unemployment rate for the county where a bank's headquarters is based. A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.

	Risk-based capital ratio							
	Extended control group				Extended treatment group			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Event×Affected	0.0074*	0.0114**	0.0105**	0.0120**	0.0076**	0.0101***	0.0073**	0.0070*
	(0.0040)	(0.0047)	(0.0050)	(0.0048)	(0.0032)	(0.0035)	(0.0037)	(0.0037)
Affected		-0.0115*				0.0095		
		(0.0067)				(0.0061)		
Credit demand			-0.0037***	-0.0030**			-0.0036***	-0.0029**
			(0.0014)	(0.0013)			(0.0014)	(0.0013)
RoA				0.0027				0.0023
				(0.0021)				(0.0021)
NPL				0.0516				0.0541
				(0.2314)				(0.2355)
Bank size				-0.0265***				-0.0249***
				(0.0070)				(0.0070)
UR				0.0974				0.0941
				(0.1016)				(0.0990)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	No	Yes	Yes	Yes	No	Yes	Yes
N. of Banks	422	422	294	294	422	422	294	294
N. of Obs.	6226	6226	3930	3930	6226	6226	3930	3930
Adj. R2	0.8892	0.0025	0.8916	0.8952	0.8895	0.0129	0.8910	0.8941
Within R2	0.0052	0.0031	0.0210	0.0541	0.0079	0.0135	0.0159	0.0446

Table O-3: Robustness - collapsed sample

This table shows results for regressions of Equation (1) in which banks' total risk-based capital ratio is the dependent variable, using a collapsed sample with mean values for the two years before and for the two years after the event. The sample includes data for all independent banks (not part of a bank holding company) in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the 2005 hurricane season (Q3 2003 to Q4 2007).
Event is a dummy variable that is zero for the pre-hurricane period and one after the hurricane season. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Credit demand is the log of a bank's volume of loan applications as reported under the *Home Mortgage Disclosure Act*. RoA is banks' return over assets. NPL/Assets represents non-performing loans over assets. Bank size is the natural logarithm of banks' number of employees. UR represents the unemployment rate for the county where a bank's headquarters is based. A detailed description of all variables is given in Table 1.
We show clustered standard errors on the bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.

	Risk-based capital ratio		
	(1)	(2)	(3)
Event	-0.0090***	-0.0090***	-0.0025
	(0.0026)	(0.0033)	(0.0044)
Event × Affected	0.0112**	0.0142**	0.0203***
	(0.0044)	(0.0066)	(0.0071)
Affected	-0.0031	-0.0023	-0.0085
	(0.0075)	(0.0083)	(0.0092)
Credit demand		-0.0071***	-0.0058**
		(0.0018)	(0.0029)
RoA			-0.0071*
			(0.0043)
NPL/Assets			0.1679
			(0.3657)
Bank size			-0.0028
			(0.0067)
UR			0.9186**
			(0.4621)
Constant	0.1733***	0.2358***	0.1955***
	(0.0048)	(0.0190)	(0.0287)
N. of Banks	258	182	182
N. of Obs.	505	338	338
Adj. R2	0.0000	0.0522	0.0702

Table O-4: Robustness - placebo event

This table shows results for regressions of Equation (1) in which banks' total risk-based capital ratio is the dependent variable, and the placebo event is placed three years before the hurricane season of 2005. The sample includes quarterly data for all independent banks (not part of a bank holding company) in Alabama, Louisiana, Mississippi, Florida, Texas, Georgia, Tennessee, Arkansas and Oklahoma over the period of ± 2 years around the placebo hurricane season of 2002 (Q3 2000 to Q4 2004).
Event is a dummy variable that is zero before the placebo event and one after the placebo event. Affected is a dummy variable that separates banks located in counties that were affected by the hurricanes (Affected=1) and banks located in counties that were unaffected (Affected=0). Event×Affected is an interaction term for the variables Event and Affected. Credit demand is the log of a bank's volume of loan applications as reported under the Home Mortgage Disclosure Act. RoA is banks' return over assets. NPL/Assets represents non-performing loans over assets. Bank size is the natural logarithm of banks' number of employees. UR represents the unemployment rate for the county where a bank's headquarters is based. A detailed description of all variables is given in Table 1.
Bank fixed effects (Bank FE) and year fixed effects (Time FE) are included in the regressions as stated in the table below. We show clustered standard errors on bank level in parentheses. The ***, ** and * stand for significant coefficients at the 1%, 5%, and 10% levels, respectively.

	Risk-based capital ratio			
	(1)	(2)	(3)	(4)
Event × Affected	-0.0000	0.0008	0.0009	0.0014
	(0.0053)	(0.0056)	(0.0056)	(0.0054)
Affected		-0.0047		
		(0.0086)		
Credit demand			-0.0032	-0.0008
			(0.0021)	(0.0020)
RoA				0.0038
				(0.0032)
NPL/Assets				0.1260
				(0.3299)
Bank size				-0.0142**
				(0.0070)
UR				0.1760*
				(0.1038)
Bank FE	Yes	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of Banks	258	258	175	175
N. of Obs.	3772	3772	2226	2226
Within/Adj. R2	0.0367	0.0059	0.0191	0.0485

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