Holding Company Affiliation and Risk: Evidence from the US Banking Sector

Radoslav Raykov and Consuelo Silva-Buston*

January 11, 2019

Abstract

Is affiliation with a bank holding company beneficial for bank stability? We revisit this question by examining the response of market-based risk measures of independent and holding-company banks to an exogenous balance sheet shock (the 2005 US hurricane season). We find evidence consistent with bank holding companies playing an important role in mitigating balance sheet shocks, with affiliates of more liquid holdings remaining more stable in terms of both systemic and individual risk. We also conduct an event study showing that markets perceive potential support from the holding as value-enhancing, as opposed to a value-reducing and inefficient cross-subsidy.

Keywords: Holding company banks; systemic risk; financial stability

JEL codes: G1, G2.

*Radoslav Raykov is at the Bank of Canada, email: RRaykov@bankofcanada.ca. Consuelo Silva-Buston is at School of Management, Pontificia Universidad de Católica de Chile, email: consuelosilva@uc.cl. Silva-Buston gratefully acknowledges the financial support of Fondecyt Iniciacion (project/folio 11150492). The views and opinions expressed are strictly those of the authors and do not represent the views of their respective institutions. The authors would like to thank Jason Allen, Ricardo Correa, Adi Mordel and Evren Damar for useful feedback. Colin Charlton and Francisca Aleuanlli provided excellent research assistance.

1 Introduction

The 2008 financial crisis has renewed interest in the main factors behind the individual and systemic risk of banks. One such factor may be holding company affiliation. The literature on holding companies shows that firms that are part of a holding differ from independent firms in several dimensions, including their capital structure (Larraín et al., forthcoming) and investments (Shin and Park, 1999). Furthermore, it has been shown that holding-company banks, in particular, differ in their lending behavior (Houston et al., 1997), risk-based capital ratios (Lambert et al., 2018) and funding sources (Campello, 2002). Thus, the stability of independent and holding-company banks is also likely to differ.

In principle, the effect of holding company affiliation on bank risk can be positive as well as negative. For example, holdings can support subsidiaries facing adverse shocks via internal capital markets (Gilbert, 1991), thereby reducing insolvency risk at troubled affiliates. Moreover, even if holdings do not channel funds to troubled subsidiaries, the market perception of an implicit support guarantee by the holding may be enough to lower the subsidiary's share price volatility. However, affiliation with a holding company could also lead to an increase in risks at subsidiary banks via higher risk-taking (Hughes et al., 1996), or via contagion from other banks in the holding (Berrospide et al., 2016). Furthermore, subsidies channeled from the parent bank to subsidiaries could be inefficient; they may promote investments in bad projects, over-investment in low-performing loans, and cross-subsidize weaker members (Scharfstein and Stein, 2000; Campello, 2002). Since these effects are not necessarily mutually exclusive, more than one effect may shape bank stability. The net effect of holding company affiliation on stability is thus not a priori clear. In this paper, we revisit this question from a new angle: we compare how holding-company-owned banks and independent banks react to an exogenous negative shock to net equity.

We study how market-based measures of systemic and individual bank risk respond to an exogenous negative shock to bank balance sheets, and whether holding company affiliation affects this response. Next we explore why this might be the case and examine whether holding company liquidity plays a role in shaping stability at holding-company banks, and whether risks spill over to unaffected holding members. We complement our understanding of bank risk with an event study analysis to examine whether market valuation after the shock differs by holding affiliation status.

As a shock, we exploit the costliest natural disaster in US history: the 2005 Atlantic hurricane season, which caused more than $162 billion worth of damage. Hurricanes reduce banks' net equity by destroying the collateral on outstanding mortgage loans, leaving banks more exposed to defaults no longer covered by assets. With the insurance sector covering significantly fewer hurricane claims than expected,[1] thousands of claimants were left without insurance payouts, affecting their ability to service outstanding mortgages and increasing bank losses.

We take advantage of the exogeneity of this shock while exploiting its similarity to a typical shock originating within the financial system, such as a financial crisis or a housing market bubble burst: a rapid and significant loss in collateral values. Taking into account the unpredictable nature of hurricane damage and its location, we use this shock as a test of the resilience of affected banks and explore how resilience outcomes differ across independent and holding-company-owned banks. The exogeneity of the shock ensures that banks' balance sheets are affected in comparable ways for both bank types, and this effect is not correlated with their inherent risk or resiliency.

Our data comes from multiple sources. We use daily stock return data from Bloomberg to compute quarterly systemic and individual risk measures (MES, SRISK, and Z-Score) and cumulative abnormal returns (CAR) for publicly traded US commercial banks. We include balance sheet and income statement variables from the banks' Reports of Condition and Income (Call Reports). Since the main impact of the hurricanes on the banks' net equity occurred through the destruction of mortgage collateral, we use the spatial distribution of bank mortgage lending to affected counties before the shock to gage bank exposures to hurricane losses. We define a continuous treatment measure, *Exposure*, as a proxy for bank losses. It equals the fraction of mortgage loans each bank extended during the pre-shock period to hurricane disaster zones designated by the US Federal Emergency Management Agency (FEMA). Treated banks are defined as those with strictly positive *Exposure*. We obtain the locations of mortgaged properties and the amount of each loan from the Housing Mortgage Disclosure Act data files (HMDA). Banks that did not extend loans to disaster zones and thus have *Exposure* equal to zero are the control group.

To identify banks belonging to holding companies, we use information from Bloomberg on the ultimate parent of each institution. We also obtain balance sheet information about holding companies from their respective FR-Y9C reports. We follow the sampled banks between 2002 and 2007 to avoid overlap with the 2008 financial crisis. The final sample

[1] For a discussion, see "The Price of Sunshine," *The Economist*, June 8, 2006, p. 76. The issue was water damage, not usually covered by hurricane policies. Moreover, at least 40% of Louisiana properties were not covered by federal flood insurance (Federal Deposit Insurance Corporation, 2005).

consists of 237 banks: 159 independent (121 non-treated, 38 treated) and 78 holding-company-owned banks (55 non-treated, 23 treated). About two-thirds of the treated banks are owned by holding companies – a variation that we use to explore differences between independent and holding-company banks.

We find that banks that are part of a holding company are more resilient to shocks than independent banks; this evidence holds in terms of both individual and systemic risk. Furthermore, our findings show that risk metrics also increase for holding company affiliates hit by the shock, but this effect is reversed as the liquidity of the holding increases. These results suggest that internal capital markets may play a role in reducing risk at holding-company banks. We also examine whether unaffected banks in affected holdings experienced spillover effects from exposed banks in the holding, as previous literature has suggested. We test whether unaffected banks in such holdings display an increase in their individual and systemic risk, but do not find a significant effect.

Our additional event study shows significant differences in the abnormal returns associated with holding affiliation. Affected holding-company banks display positive abnormal returns after the shock; while affected independent banks display negative abnormal returns after the shock. These results suggest that holding company dynamics after the shock are perceived as beneficial by the market in the form of value-enhancing (potential) support from the parent; and not as value-reducing inefficient subsidies, as suggested in a previous literature (Scharfstein and Stein, 2000; Campello, 2002). Furthermore, the abnormal returns of unaffected banks in affected holdings show a negative impact during the first days after the shock. This suggests a negative market reaction consistent with the perception of reduced parental support or fewer resources available to unaffected affiliates.

Our main identification comes from a difference-in-difference approach. This identification relies on two assumptions: that there are parallel trends for the treated and the control group, and that the treatment assignment is exogenous to the outcome of interest. We provide tests that support the validity of both assumptions in our setting.

Our empirical setting complies well with the parallel trend assumption. To support this, we show graphically that there are no prior trends in systemic or individual risk that may explain our findings. In addition, we also run a placebo test defining the shock half a year earlier than its true date. The placebo test confirms our results: changes in systemic and individual risk occurred only after the real shock and not prior to it.

The treatment assignment is exogenous to the banks' risks in our setting. To confirm this, we first note that hurricanes are exogenous phenomena. Even though areas commonly subject to hurricanes may differ in a systematic way from the rest – something that our model accounts for by bank fixed effects – the timing, the specific areas, and size of the damage is still a priori unknown. Secondly, we show that our results are robust by controlling for time-varying observable characteristics. And thirdly, our results are not driven by imbalances in observable characteristics between the control and the treated group. We match treated banks to control banks based on observable characteristics (size, state, and holding affiliation); our results continue to hold when restricting the estimation to this matched sample.

We contribute to the existing literature along several dimensions. Our first contribution is to the literature studying the benefits and costs of holding company affiliation. This literature has studied the effects on both financial and non-financial firms. The benefits from internal capital markets in holding companies have been widely studied in the non-financial firms literature (e.g., Almeida et al., 2015; Bena and Ortiz-Molina, 2013, and Gopalan et al., 2007). This literature argues that group affiliation can relax financial constraints by channeling funds to troubled firms. Consistent with internal capital market benefits, Shin and Park (1999) show that holding affiliation reduces firm investment sensitivity to cash flows. The same study also shows that firm investment is related to the cash flows of other firms in the holding. Internal capital markets may also enable member firms in the holding to share the risks through the reallocation of resources, which may affect their cost of financing. Byun et al. (2013) show that the co-insurance resulting from group affiliation lowers the cost of public debt. On the other hand, holding company affiliation may also lead firms to engage in unproductive activities, overinvest in low-performing industries and cross-subsidize weaker members (Ferris et al., 2003).

With respect to financial firms, the literature has studied the effect of holding company affiliation on lending (e.g., Houston, et al. 1997), access to federal funds and CD markets (Campello, 2002), capital injections (Gilbert, 1991) and risk-based capital (Lambert et al., 2018). The closest paper to ours in this literature is Ashcraft (2008). Ashcraft studies the relationship between holding company affiliation and supervisory CAMEL ratings, and, in line with our results, documents that holding-company banks are safer than independent banks. He argues that this is driven by higher capital injections and access to funds by holding subsidiaries. We improve on this literature in two ways. Firstly, we eliminate concerns about shock endogeneity by using a natural disaster to create exogenous variation in banks' net equity, and study banks' resilience; secondly, we use higher-frequency, more granular market-based measures, which have been shown to predict more accurately banks' future performance than CAMEL ratings (Berger, Davies, and Flannery, 1998; Cole and Gunther, 1998). Furthermore, market data allows us to examine an additional channel, not yet studied in this literature, through which holding affiliation could affect banks' performance and risk: the market perception of holding company dynamics after a negative shock.

Our paper also contributes to the literature studying the determinants of bank stability. This literature has focused on the effects of bank characteristics (e.g., Laeven et al., 2016; De Jonghe, 2010), banking system competition levels (e.g., Beck, 2008, Anginer et al., 2014) and country characteristics (Anginer et al., 2014). We study how holding company affiliation affects banks' risk resiliency in terms of individual and systemic risk. To the best of our knowledge, this is the first paper to study this relationship.

Our work is also related to the literature studying the effects of natural disasters on bank behavior. This literature has focused on the effects on credit supply after a shock. Garmaise and Moskowitz (2009), for example, show that insurance market imperfections can restrict the supply of credit in damaged areas, while Cortés and Strahan (2017) find that real estate lending increases. Moreover, this credit is mostly supplied by affected banks (Chavaz, 2016; Cortés and Strahan, 2017). Lambert et al. (2018) show that risk-based capital ratios increase for independent banks after the shock. In addition, they show evidence that independent affected banks increase government securities holdings and reduce loans to non-financial firms when adjusting their capital ratios. Finally, Noth and Schüwer (2017) and Klomp (2014) examine the effect of natural disasters on individual bank stability. The former paper focuses on the probability of bank failure in the US following a natural disaster. The latter paper examines the effects on a bank's distance to default at the country level. Both find evidence showing that individual risk increases following a disaster, as expected. In this paper, we extend this literature and explore systemic stability at banks following a natural disaster. Furthermore, we also examine the heterogeneous effect that holding company affiliation may have on bank risk.

Finally, this paper is also related to the literature on geographic diversification and risk (e.g., Demsetz and Strahan, 1997; Chong, 1991; Acharya, Hasan, and Saunders, 2006; Deng and Eliyasiani, 2008) and the geography of bank lending (Petersen and Rajan, 2002). To the extent that multibank holdings are geographically more diversified than independent banks, which are more likely to be local, our results are consistent with previous findings showing that geographic diversification reduces risk (for example, see Goetz et al., 2016). However, diversification per se does not explain our results; we control for this factor in a series of robustness tests. Instead, we study how holding company affiliation affects bank risk.

The remainder of the paper is structured as follows. The next section provides background information about the 2005 hurricane season. Section 3 describes our data and treatment identification. Section 4 describes our empirical strategy and results. Section 5 concludes.

2 Background on the 2005 hurricane season

Hurricanes Katrina, Rita, and Wilma, which formed the bulk of the 2005 Atlantic hurricane season, made landfall in the US Gulf Coast between August 29 and October 27, 2005. Collectively, these three hurricanes inflicted the largest recorded damage in US history: US $162.5 billion. The largest chunk of the damage was caused by Katrina ($125 billion), followed by hurricanes Wilma ($19 billion) and Rita ($18.5 billion) (National Hurricane Center, 2018). Hurricane Katrina affected Alabama, Florida, Louisiana, Mississippi, and parts of Arkansas, with the heaviest impact in Louisiana and Mississippi. Hurricane Rita affected Louisiana and parts of Texas, while Wilma affected mostly southern Florida. The three hurricanes put a strain on banking operations, insurance companies, businesses and individuals in the affected areas. Damage across multiple states, together with repeated hits to Louisiana, made the scale of destruction unprecedented; large parts of New Orleans were flooded. The catastrophic impact of the hurricanes was felt throughout the region and destroyed assets totaling nearly 1.25 % of the US annual GDP for 2005. Many of the lost assets were real estate owned or mortgaged by banks, which increased their losses and deflated their balance sheets.

Specifically, the hurricane season reduced banks' net equity by destroying the collateral on outstanding mortgage loans, leaving banks exposed to loan defaults no longer collateralized by assets.[2] With the insurance sector covering significantly fewer hurricane claims than expected, thousands of claimants were unable to collect insurance and service their mortgages.[3] The resultant loss of physical assets increased bank mortgage losses, and the share of nonperforming loans grew. This is displayed in Figure 1, showing the nonperforming loan ratios for the affected and the control banks in our sample (we define these two groups more precisely in section 3.1).[4]

Figure 1 shows a clear downward trend in nonperforming loans for both affected and

[2]Lenders do not have an automatic legal right to insurance payouts or aid paid to the borrower, even if he is in default. (Federal Financial Examination Council, 2005).

[3]The legal issue behind this was whether wind-driven water damage qualifies for hurricane insurance. Many insurers denied coverage arguing that water damage came first (see "The Price of Sunshine," *The Economist*, June 8, 2006).

[4]Nonperforming loans are computed as the ratio of loans past due for 30+ days but still accruing interest and nonaccrual loans to total loans.

unaffected banks prior to the shock, consistent with the recovery from the 2001 recession. For unaffected banks, this trend continues all the way to 2006, when mortgage default risks foreshadowing the 2007 financial crisis slowly began to build up. However, for the affected banks, this downward trend reverses much earlier – in August 2005, when hurricane Katrina made landfall. For the next ten months, affected banks display a notably higher fraction of nonperforming loans than control banks, with the two groups converging approximately twelve months after the shock, consistent with Cortés and Strahan's (2017) estimate of the duration of the hurricanes' economic effect. Towards the end of the sample period, nonperforming loans for both control and affected banks start trending back to their 2004 levels, reflecting the gradual buildup of risk leading to the 2007-08 crisis. The disparity between loan performance at affected and control banks, its duration and timing are fully consistent with prior research.

3 Data

We combine data from multiple sources to study the effect of the 2005 hurricanes on bank risk and returns. We use the Bloomberg database to retrieve the stock prices of 909 commercial banking entities to compute our main dependent variables (Z-Scores, MES, SRISK, and CAR). We match this data by name to the Reports of Condition and Income (Call Reports) to obtain bank balance sheet and income statement variables. We are able to match 581 out of 909 Bloomberg entities to their corresponding Federal Reserve RSSD identifiers used in Call Reports. Out of these entities, 252 are holdings issuing group-level stock, and 329 are banks for which we compute market-based risk measures.

The counties affected by the 2005 hurricane season are identified from FEMA's official disaster declarations. Affected banks are identified as those with mortgage lending exposure to counties where disaster has been declared (see subsection 3.1); the counties of each bank's mortgage lending are sourced from the HMDA data files, which contain the geographic location of each mortgage loan. Since Call Report bank identifiers (RSSD ID numbers) are not reported in the HMDA prior to 2004, we match the Call Report and HMDA datasets based on RSSD ID's reported in both datasets for 2009 – the year with the highest number of matched banks, using the Call Report bank names to check back in time for RSSD ID changes. This results in 294 matched banks, or 82% of the Call Report sample. We limit the sample period to six years (2002-2007) to avoid overlap with the financial crisis starting in 2008; the sample selection is explained in subsection 3.1. A full description of the variables and their sources is given in Appendix A.

3.1 Treatment definition

Since the main impact of the hurricane season on banks occurred through the destruction of mortgage collateral, we use each bank's mortgage lending to disaster counties before the shock as an exposure metric for its hurricane-related losses. Berrospide et al. (2016) document that 21% of the mortgage loans in the HMDA dataset were extended to areas without physical branch presence; hence, destroyed mortgage collateral in hit counties is likely a more accurate proxy of a bank's hurricane exposure than its physical branch presence.[5]

We define a continuous treatment measure, *Exposure*, to identify the affected banks. For each bank, *Exposure* equals the fraction of mortgage lending it extended between 2002 and 2004 to disaster counties; the loan amounts and locations are obtained from the HDMA data. The results are not sensitive to whether we define mortgage lending as mortgage originations or as unsold mortgages remaining in the bank's portfolio (also known as portfolio lending); the robustness of this measure is discussed in section 4.1.3. Banks that did not lend to disaster counties during the pre-hurricane period and thus have an *Exposure* equal to zero are the control group in our setting.

We identify the disaster counties as those officially designated by FEMA for individual disaster assistance as for September 28, 2005 (for hurricanes Katrina and Rita) and November 8 (for hurricane Wilma). Individual assistance is offered in counties where homes have been damaged or destroyed; it strongly correlates with bank risk exposure. By contrast, counties receiving only public assistance for infrastructure repairs have some uncertainty about the treatment effect.[6] To ascertain that the control group is not contaminated by banks with exposure to uncertain-treatment counties, we further clean up the control group by excluding several banks with mortgage exposure to such borderline counties. This excludes 18 control banks without materially changing the size or the composition of the control group, which remains sufficiently large (176 banks) and diverse.[7]

FEMA's designation of disaster counties from the 2005 hurricane season is shown in red

[5]This also relates to the correlation between deposit and lending markets (Petersen and Rajan, 2002).

[6]For example, public works in central and western Texas and east Arkansas were limited to clearing roads and reconnecting power lines.

[7]The excluded banks are: BancFirst, Bank of the Ozarks, Beach First National Bank, Cherokee Bank, Citizens Union State Bank and Trust Co. (subsequently Hawthorn Bank), Colony Bank of Fitzgerald, Community State Bank, Fauquier Bank, First National Bank of Shelby, Great Southern Bank, Integrity Bank, Merchants Bank, Middlefield Banking Co., Mountain National Bank, New Peoples Bank, Pacific Mercantile Bank, Simmons First National Bank, and Southeastern Bank. To alleviate any concerns about differences between the treated and the control group, we repeat our regressions with propensity score matching in Section 4.1.3 and show that the results are robust.

in Figure 2. Based on this figure, a bank is defined as treated if it had positive mortgage lending to a treated (red) county during 2002-2004 (that is, if the bank's *Exposure* is larger than zero).

To facilitate longitudinal comparisons, we include only banks that were in the sample before the disaster. Thus the final sample consists of 237 banks: 159 independent (121 non-treated, 38 treated) and 78 holding-company-owned banks (55 non-treated, 23 treated). About two-thirds of the treated banks are owned by multibank holding companies – a variation that we use to explore differences between independent and holding-company banks.

Table 1 lists the number of bank-quarter observations for our sample (bank-years from 2002 to 2007) across treated and control groups, and across independent vs. holding-company banks. Table 2 provides summary statistics of the *Exposure* variable in our sample. Our sample includes both local (state and county) banks, as well as big multistate banks.

4 Empirical analysis

The objective of this analysis is to examine the relation between bank risk, abnormal returns, and holding affiliation, while controlling for a number of factors. To measure risk and returns, we focus on market-based measures that contain higher-frequency and more granular information than the CAMEL supervisory ratings used by previous studies (Ashcraft, 2008). Market-based measures have been shown to more accurately predict bank performance going forward (Berger, Davies, and Flannery, 1998; Cole and Gunther, 1998), which is important for capturing the aftermath of the hurricane season. More importantly, market data incorporates the perception of stockholders about bank dynamics after the shock, which provides valuable information and allows us to draw additional inferences about mechanisms other than the functioning of internal capital markets through which holding company affiliation could affect bank performance and risk, such as implicit guarantees and inefficient cross-subsidization.

4.1 Holding company affiliation and risk

We first analyze the role of holding companies in shaping the effect of a negative shock on bank risk. For this, we construct market-based measures of both systemic and individual bank risk. We use marginal expected shortfall, or MES, (Acharya et al., 2017) to measure systemic risk, whereas at the individual bank level, we use market Z-Scores. Although our results are consistent across both metrics, they do not measure the same thing; while the market Z-Score captures a bank's insolvency risk, MES captures the comovement between the bank and the rest of the financial system.

4.1.1 MES and Z-Score

Following Acharya et al., (2017), MES calculates the expected capital shortfall of an individual bank i, conditional on the rest of the financial system experiencing distress. MES for a bank i is constructed quarterly as the average of i's daily returns, taken over the days where the remaining banks' returns are within their worst 5% for each quarter. For each bank i, we therefore construct a daily index of the remaining banks' prices, and average i's returns over the worst 5% of this index's returns. Specifically, if $R_{i,d}$ is the return of bank i on day d, then this bank's MES for quarter t is defined as

$$MES_{i,t} = \frac{1}{|I|}\sum_{d \in I} R_{i,d}, \quad \text{where} \quad I = \{\text{worst 5\% of days for the returns of } Index_{i,d}\}, \tag{1}$$

where $Index_{i,d}$ is a value-weighted index of all banks in the banking system excluding bank i to avoid a mechanical relation between the bank's return and the index return.

By contrast, the traditional market Z-Score metric captures a bank's individual resilience without conditioning on the rest of the system. We compute each bank's quarterly market Z-Score following Lepetit et al. (2008) as 1 plus the bank's average daily return over the quarter, divided by the quarterly standard deviation of the bank's return:

$$\text{Z-Score}_{i,t} = \frac{1 + \mathbb{E}R_{i,d}}{\sigma_{R_{i,d}}}. \tag{2}$$

These two metrics provide information about both the individual level of risk attained by each bank and its comovement with other affected banks after the shock. We provide descriptive statistics of these risk measures based on data of the pretreatment period in Table 2. Panel A summarizes the full sample, Panel B summarizes the statistics for independent banks, and Panel C summarizes the statistics for holding-company banks.

In the full sample (Panel A), the average Z-Score for the control group is 55.98, with a standard deviation of 33.94. The MES in this group has a mean of 0.00035 and a standard deviation of 0.031. Affected banks have a slightly higher Z-Score of 64.47, with a standard deviation of 27.99. This group also displays higher MES, with a mean of 0.009 and standard deviation of 0.019. Standardized differences suggest that the treated group has lower individual risk, but higher systemic risk. To reduce differences between these groups, we match treated and control banks on pretreatment characteristics. Matching ensures common support on the observed matching variables. We match banks according to size, holding company affiliation and by state, using four years of pre-shock data. We present the summary statistics of the matched sample in the last five columns of Table 2. The last column in the table shows that the treated and control group display similar characteristics after the matching. Thus, the matching procedure produces a balanced sample. We estimate a robustness test based on this matched sample.

Using Z-Score and MES measures, we study the relationship between holding company affiliation and risk. To this end, we estimate variations of the following panel data model:

$$
\begin{aligned}
Risk_{it} = \alpha_0 + \sum_i \alpha_{1,i} d_i + \alpha_2 Post_t + \beta_1 Exposure_i * Post_t + \beta_2 Post_t * Independent_i \\
+ \beta_3 Exposure_i * Post_t * Independent_i + \sum_k \gamma_k X_{k,i,t} + \epsilon_{it},
\end{aligned} \tag{3}
$$

where $Risk_{it}$ equals either the bank's individual risk $Z\text{-}Score_{it}$, or its systemic risk MES_{it} in quarter t. $X_{k,i,t}$ are bank-specific covariates. The period before the shock in our sample spans from 2002 to the second quarter of 2005, while the *Post* period spans from the third quarter of 2005 to the end of 2007.[8] We exclude the crisis period to avoid biases arising from changes in bank behavior. However, our main results regarding the role of holding company affiliation are robust to longer time periods.

The variable $Exposure_i$ is a continuous bank-level variable ranging from 0 to 1, defined as the bank's mortgage lending share to affected counties during the three years preceding 2005.[9] Our setting is a difference-in-difference approach; thus, the coefficient β_1 in equation (3) captures the differential effect for the banks hit by the shock (i.e., exposed banks) over banks that were not hit (i.e., control banks).

We are interested in the role that being part of a holding company has on bank risk. Therefore, we further interact the fourth term in (3) with a dummy variable indicating whether the bank is independent, $Independent_i$. We define a bank as independent if it

[8] We do not include time dummies in our baseline models since we are also interested in the shock's average effect across all banks. The previous literature has studied whether unaffected banks responded by increasing lending to affected areas (e.g. Chavaz, 2016); this could also affect the unaffected banks' risk. As a robustness test, however, we do include county-year fixed effects.

[9] The results are not sensitive to whether we define mortgage lending as mortgage originations or as unsold mortgages remaining in the bank's portfolio; the robustness of this measure is discussed in section 4.1.3.

does not have a parent bank according to the Bloomberg database. Our coefficient of interest is then β_3, which captures the differential effect on affected independent banks over affected holding-company banks.

We also include bank fixed effects d_i in all models to control for time-invariant unobserved characteristics.[10] The hurricane season is also likely to have affected other bank covariates. Therefore, we do not include bank controls in the main regressions; we are interested in the differential effect on affected independent banks without partialling out the effect that the shock had on other covariates.[11] In a set of robustness tests, we include bank controls that are commonly used in bank stability literature (e.g., Brunnermeier et al., 2012). These controls are the logarithm of the assets, leverage, return on assets (ROA), non-interest income as a share of total income, and loan (quarterly) growth.

The identification of causal effects in our difference-in-difference strategy rests on two key assumptions: that there are parallel trends for affected and control groups; and that the treatment assignment is uncorrelated with changes in the outcomes of interest. We take these assumptions as valid for now and discuss their validity in our setting in Section 4.1.3.

4.1.2 Main results

The results of our panel data model are shown in Table 3. We first study the effect of the shock on individual and systemic risk without taking into account the role of holding affiliation. Results for these models are presented in columns (1) and (2) in this table. The *Post* dummy enters with a positive sign and is statistically significant in the Z-Score model in column (1). This suggests that on average, insolvency risk decreased for all banks after the second half of 2005. We do not find any significant effect of the negative shock on the individual risk for affected banks relative to control banks in this column. This is shown by the coefficient of the interaction term of the *Post* and *Exposure* variables, which is not significant. The model for systemic risk displays similar results. Column (2) likewise does not show any significant effect of the negative shock on the MES for affected banks relative to control banks. These results are puzzling, as one would expect a big negative shock to bank balance sheets to have an impact on their risk. In particular, one would expect an increase in insolvency risk, driven by the large credit losses experienced

[10]The inclusion of bank fixed effects captures all time-invariant differences between banks. Therefore, time-invariant interaction terms originated by the triple difference are dropped out in these models. These dropped terms are $Exposure_i$, $Independent_i$ and $Independent_i * Exposure_i$.

[11]Including covariates that are likely to be affected themselves can lead to biases in the coefficient of interest (Angrist and Pischke, 2009).

by banks after the disaster.[12] The effect on systemic risk is less clear. On the one hand, a local negative shock may decrease correlatedness with other banks in the US; on the other, as a response to the shock, banks could also take actions that increase their correlatedness with the other banks in the system.

These puzzling findings suggest that the aggregate effect might be masking heterogeneity based on bank type. The literature on multibank holding companies has shown that banks that are part of a holding company behave differently from those operating as independent banks, so their stability is also likely to differ. The effect of holding company affiliation on risk can be positive as well as negative. For example, parents can support subsidiaries facing adverse shocks via internal capital markets (Gilbert, 1991), thereby reducing insolvency risk at affected affiliates. Moreover, even if parent banks do not channel funds to subsidiaries, the perception of an implicit guarantee of support may stabilize the affiliate's share price volatility. However, holding affiliation can also lead to an increase in risks via higher risk-taking (Hughes, et al., 1996), and thus make it more difficult for affiliates to withstand a negative shock, or via contagion from other banks in the same holding (Berrospide et al., 2016). Moreover, parental subsidies can be perceived by the market as inefficient and increase the affiliate's share price volatility (Campello 2002; Scharfstein and Stein, 2000). Thus, regardless of how the shock affects independent banks, the impact on holding-company banks is likely to be different. If the impact across these two groups is opposite, this could explain the insignificant results in columns (1) and (2).

We account for this in the next two columns by including a triple interaction term with an indicator for independent banks. We find that the shock worsens individual insolvency risk, as shown by the negative sign of the triple interaction term in the model in column (3). The coefficient equals -47.59 and is significant at the 5% level. The effect is also economically significant; a 10-percentage-point increase in an independent bank's exposure leads to a decrease in its Z-Score of 4.7 or 0.14 (4.7/34.6) standard deviations. The evidence for holding-company banks suggests that their insolvency risk is not significantly affected by the negative shock, as can be seen in the interaction term of the *Post* and *Exposure* variables in this model. The coefficient equals 27.67 but is not statistically significant. A decrease in Z-Score implies an increase in insolvency risk; hence, our results suggest that independent banks face increased insolvency risk after the

[12] Although some banks received large inflows of insurance payments and government aid during this period, Noth and Schüwer (2017) find that this did not offset the negative effect of the hurricanes. This seems plausible, as least 40% of the flooded properties in Louisiana were not covered by federal flood insurance (Federal Deposit Insurance Corporation, 2005).

shock, while the insolvency risk of holding affiliates is unaffected.

Regarding systemic risk, we find a stronger positive effect for independent banks than for holding-company banks in column (4). The coefficient of the triple interaction equals 0.05 and is significant at the 5% level. The effect on systemic risk is also economically significant; a 10-percentage point increase in an independent bank's exposure increases its MES by 0.005. This corresponds to an increase of 0.21 (0.005/0.024) standard deviations. The effect for holding-company banks is only weakly significant, as shown by the interaction term between the *Post* and *Exposure* variables. The coefficient equals -0.03, but is significant only at the 10% level. These results suggest that systemic risk increased only for independent banks affected by the shock, and not for banks that are part of a holding.

The above results show that banks that are part of a holding company are more resilient to shocks than independent banks. This could be either because internal capital markets enhance their stability, or because implicit guarantees affect the market's perception. We focus on the market reaction in the immediate aftermath of the shock in Section 4.2; but first, we examine the holding dynamics in more detail in Section 4.1.4 and study whether holding company characteristics exacerbate or mitigate the resiliency of holding affiliates, and the effects on other banks in the same holding. Before doing that, we provide evidence that our differences-in-differences approach complies with the necessary assumptions and present additional evidence that our main results are robust.

4.1.3 Robustness

In this section, we first test the validity of the two key assumptions needed to establish causality in our difference-in-difference strategy: that there are parallel trends for treated and control groups, and that the treatment assignment is uncorrelated with changes in the outcomes of interest. In this exercise, a bank is defined as treated if it had positive mortgage lending to an affected county for the years 2002-04 (i.e., banks with $Exposure > 0$).

We first note that the shock in our model – the 2005 Gulf coast hurricane season – is exogenous. Therefore, the validity of our key assumptions should not be a concern. It could be argued, though, that hurricanes are common in certain areas in the US, which might lead to systematic differences between banks lending in those areas with respect to the rest. These differences, however, are time-invariant, which in our setting is captured by bank fixed effects. In addition, even though hurricanes might be common in some areas, their exact timing is unknown; the specific areas they affect, and, more importantly, the size of the damage, is unexpected.

We discuss alternative explanations for our results and perform a set of additional robustness tests.

Parallel trends. We explicitly examine bank-level differences in trends for treated and control banks. First, we graphically examine the trends for both groups of banks. For this, we run a regression of the Z-Score, controlling only for bank fixed effects and state-year fixed effects, using data from 2000 to 2010. We obtain the residuals of this regression and average them within each group-year. We run this regression separately for independent and holding-company banks. Figure 3 shows the evolution of the average residuals for independent and holding-company banks. The figure shows that there is no clear upward or downward trend in the Z-Score of independent banks in the years prior to the 2005 hurricane season; this is also the case for holding-company banks. The parallel trend assumption for the Z-Score is therefore supported by this evidence. This figure also shows a slight decrease in the Z-Score after the shock; this decrease is more pronounced for independent banks.

We perform the same exercise for the systemic risk measure, MES. Figure 4 shows the evolution of the average residuals in this case. As with the Z-Score, MES does not display a clear upward or downward trend for independent banks prior to the hurricane season; this is also the case for holding-company banks. The parallel trend assumption for the MES is also supported by the evidence.

We also run a placebo test, whereby we shift the shock and the sample time frame by half a year earlier. Our sample thus spans from 2001:Q3 to 2007:Q2, and we define the *Post* dummy to be equal to one from the beginning of 2005 (the variable *Post placebo* in Table 4). In the event of parallel trends between affected and control groups, our results should not survive this test. Thus, the interaction and triple interaction terms should not enter significantly in these regressions. The first two columns in Table 4 display the results of this test for the Z-Score and MES, respectively. The results are not significant when shifting the shock half a year earlier. Therefore, the conclusion from our graphical test is upheld, and the parallel trends assumption holds in our setting.

Treatment assignment. Control and affected banks in our sample differ in their observable characteristics, as shown by the standardized difference in the fifth column of Table 2. In particular, treated banks seem to be larger and more leveraged, and invest in a larger share of non-interest income activities. However, these differences in their observables are not driving our results. To show that this is the case, we first control for time-varying characteristics commonly used in the bank stability literature, in columns (3) and (4) of Table 4. The evidence from these models shows that our results remain unchanged when controlling for the above covariates. Therefore, the results presented above are not driven by omitted observable characteristics. Among the controls added, size, as proxied by the logarithm of assets, shows to be positively related with systemic risk, in line with results found in previous literature (e.g., Laeven et al., 2016).

Second, we test the robustness of our results using propensity score matching to match treated banks to similar banks from the control group. We estimate our model using the matched sample in columns (5) and (6) of Table 4; our results continue to hold. Thus, imbalances between control and treated banks do not explain our results.

Finally, one remaining concern is that independent banks might be more exposed to affected coastal regions than holding-company banks. To account for this concern, we include county-year fixed effects to compare the different bank types within the same county-year. Results are shown in the last two columns of Table 4. Our results remain unchanged when controlling for this fact.

Other robustness tests and discussion. We have found evidence that holding-company banks are more resilient to a negative shock than independent banks. However, holding-company-owned banks may be more geographically diversified than independent banks, which could also explain the higher resiliency of holding affiliates. We additionally explore whether the differential effect of the shock on independent banks captures the effect of geographic diversification instead of holding company affiliation. We test whether this is the case by computing a geographic concentration index, HHI_{div}, defined at the holding level as the Herfindahl index of mortgage loans across counties.[13] A higher HHI_{div} implies higher geographic concentration and, thus, lower geographic diversification in lending. We show the results of this test in Table 5. In the first two columns, we replace the holding company affiliation dummy by the bank geographic diversification measure, HHI_{div}. The simple interaction term capturing the effect of the shock on risk for affected banks suggests that individual and systemic risk both increased after the shock as expected, as indicated by the models in columns (1) and (2). The results also suggest that banks in less-diversified-holdings lending to affected areas before the shock also dis-

[13] HHI measures are standard in the geographic diversification literature. For recent examples, see Goetz et al. (2016) or Deng and Elyasiani (2008), among others.

play higher insolvency risk, as suggested by the negative and significant coefficient of the interaction term $Exposure * HHI_{div}$ in the model (1). The triple interaction term, however, is not significant at 5% in these models, suggesting that geographic diversification neither exacerbates nor mitigates the effect of the negative shock on bank risks.

In the last two columns, we include both triple interactions ($Post * Independent * Exposure$ and $Post * HHI_{div} * Exposure$). Columns (3) and (4) show that the triple interaction with holding affiliation is highly significant in both models, and with the expected signs, whereas the triple interaction with the geographic diversification measure HHI_{div} is not significant. This confirms that the factor driving the differential effect for holding-company banks is their affiliation with a holding and not higher geographic diversification.

Lambert et al. (2018) show evidence that affected independent banks increased their risk-based capital ratios once hit by hurricane Katrina, while holding-company banks did not. Higher capital ratios ought to make independent banks safer after the shock, contrary to what we found in the previous section. This suggests higher capital ratios alone do not explain our results; nevertheless, we further show that this is the case in Table 6 by controlling for this explicitly. In the first two columns of Table 6, we replace the independent dummy by the banks' risk-based capital ratios. In column (1), only the interaction between $Post$ and $Capital\ ratio$ shows to be statistically significant at 5%. The positive coefficient in this interaction term suggests that after the shock, higher-capitalized banks experienced lower insolvency risk. In the second column, the negative and statistically significant (at the 1% level) estimate of the capital ratio suggests that higher-capitalized banks displayed lower systemic risk. The triple interaction term, which is not significant in either model, suggests that even though hit independent banks may have increased their capital ratios, the better-capitalized ones did not display a significantly different risk differential after the shock. Next we add to this model the interaction terms $Post * Independent$ and $Post * Independent * Exposure$ in columns (3) and (4) of this table. The added triple interaction term enters with the expected sign, increasing insolvency and systemic risk for affected independent banks after the shock, and it is statistically significant in both models; whereas the triple interaction term with capital ratios remains insignificant in all models. Thus, changes in the capital ratios of independent versus holding-company banks do not drive our results.

Another concern is that independent and affiliated banks may differ in several dimensions other than their holding affiliation. This concern is partially accounted for with bank fixed effects that control for any time-invariant difference between these two types of banks, and with the inclusion of bank controls in the models in Table 4. We further account for these differences and use propensity score matching to match independent banks to similar affiliated banks. For this, we match banks according to size, state, and treatment status, using four years of pre-shock data. We show the results of these estimations in Appendix B. Our results hold when using this matched sample. Hence, differences between independent and holding company banks do not seem to explain our results.

We also test whether a different definition of risk affects the robustness of our results. For this, we compute an alternative measure of systemic risk: the SRISK (Brownlees and Engle, 2017). The SRISK measures the exposure of an individual bank to systemic risk by computing the expected capital shortfall of a financial entity, conditional on a prolonged market decline. Specifically, the SRISK is computed as follows:

$$SRISK_{it} = W_{it}\left[kLVG_{it} + (1-k)LRMES_{it} - 1\right], \tag{4}$$

where W_{it} is market equity, k is the prudential capital fraction set equal to 8%, and LVG_{it} denotes the quasi-leverage ratio (that is, the sum of book debt and market equity over market equity). $LRMES_{it}$ is the long-run MES, which we approximate as $LRMES = 1 - e^{(-18*MES)}$ following Acharya et al. (2012).

The results using this measure are presented in Appendix C. Results in columns (1) and (2) in this table support our results from the previous section. We do not find any effect on risk for affected banks when we do not control for their holding affiliation. However, allowing a differential effect for independent versus holding-company banks shows that independent banks are more fragile when facing negative shocks, as shown by the triple interaction term, which enters with a positive sign and is significant at the 5% level. Results also hold when controlling for time-varying covariates in column (3).

Finally, we also run a couple of unreported tests. First, since we argue that the channel through which banks are negatively affected by the shock are the losses they incur from outstanding mortgages, we adjust our $Exposure$ variable to include only unsold mortgages. If the bank sells the loan, it removes this risk from its portfolio, and is no longer exposed to the respective losses. The distribution of this variable is highly similar to the original measure (the correlation between the two variables is 0.9), and it is not highly correlated with affiliation or treatment status. Thus, as expected, our results remain unchanged when using this alternative treatment variable. Second, we estimate our risk model focusing on holding company banks only and examine whether having an insurance company in the holding affects our results. Holding companies that have an insurance company in the group may have experienced higher losses than the others as a result of large insurance payments. This heterogeneous effect could be biasing our results towards not finding a significant result for holding-company banks as a whole. For this, we create a dummy variable equal to one if the bank has at least one insurance company in the holding.[14] We do not find any differential effect for such holdings. Our previous results remain unchanged.

4.1.4 Understanding holding-company banks' dynamics

The previous sections show that risk metrics increase when banks face a negative balance sheet shock. However, we find this effect to be statistically significant only for independent banks. In this section, we aim to further understand holding company mechanics and examine whether holding company characteristics play a role in bank resiliency, and whether there are spillover effects within holdings.

Our first set of tests examines whether the holding's liquidity plays a role in shaping stability at holding-company banks. Previous literature on holding companies suggests that the lending activity of holding affiliates is sensitive to the holding's liquidity (e.g., Houston et al., 1997).[15] It argues that in the presence of market frictions, which create a wedge between internal and external funds, holding companies manage funds at the holding-wide level, allocating scarce resources among the subsidiaries and conditioning their investments on the holding's liquidity. Thus, observing that holding liquidity mitigates the effect of the negative shock would be consistent with internal capital markets playing a role in determining bank stability.

In our second set of tests, we study spillover effects on other banks in the holding. Internal capital market operations within the holding may affect investments across several markets, rather than concentrating on the affected market only (e.g., Berrospide et al., 2016).[16] This literature argues that when relative profitability changes, banks either move resources from one market to another, or cut investments in all markets in response to a single-market shock. In either case, one would expect to see an effect on the risk of unaffected holding company members. Moreover, even if the parent does not move resources away from unaffected affiliates, the market's perception that fewer resources are now available to them could already increase their stock's volatility. We examine whether

[14] We exclude from this dummy life insurance companies as they do not cover housing damages.

[15] This has also been shown by Shin and Park (1999) for non-financial firms.

[16] Evidence of the existence of such spillovers has also been shown for non-financial firms. Gopalan et al. 2007 show that a single default of a firm in a group leads to a decrease in investments, external funding, and profits, and it increases the probability of default of all firms in the group.

this is the case.

4.1.4.1 Holding-company banks and holding liquidity

We first examine whether resiliency depends on the holding's liquidity. For this, we estimate our model on the holding-company banks only and include a triple interaction between the *Post* and the *Exposure* variables with the holding's liquidity (cash and balances from depository institutions as a share of assets).[17] Table 7 shows the estimation results from these models. The first two columns study the effect of the holding's liquidity on the Z-Score and MES metrics, respectively. The estimate of the interaction of the *Post* and the *Exposure* variable is now negative and significant at the 5% level in column (1), whereas the triple interaction term is positive and significant at the 5% level. This result indicates that individual insolvency risk increases for shocked holding affiliates, but this negative effect is reversed as the liquidity of the holding increases. In particular, a 10-percentage-point increase in the liquidity of the holding (as a share of assets) leads to an increase of 20.8 in Z-Score.[18] This corresponds to an increase in 0.6 (20.8/32.4) standard deviations. The holding's liquidity level displays a negative and significant coefficient, suggesting that, absent a shock, higher liquidity at the holding level increases the subsidiary's insolvency risk, consistent with the literature showing that excess liquidity correlates with higher risk of a hostile takeover (Blanchard et al. 1994) and has tax and accounting costs (Jaffee and Russell, 1997). This result likely reflects the opportunity cost of holding a larger amount of very liquid assets.

Results for the MES are in line with the evidence for the Z-Score. The simple interaction estimate in column (2) is positive and significant at the 5% level, whereas the estimate of the triple interaction term is negative and significant at the 5% level. These estimates suggest that systemic risk increases when holding-company banks are affected by a shock, but this is also reversed as the liquidity of the holding increases. In particular, a 10-percentage-point increase in the holding's liquidity as a share of assets reduces MES by 0.05. This corresponds to a decrease in 2.5 (0.05/0.02) standard deviations. Taken together, these results suggest that internal capital markets may play a role in reducing risk at holding-affiliated banks.

Liquidity buffers are likely to be correlated to other holding characteristics that may affect bank risk. We account for this fact and include holding company level controls in the

[17] Previous literature on holding companies suggests that the lending activity of holding affiliates, which is the biggest source of risk for a traditional bank, is sensitive to the holding's liquidity (Houston et al., 1997); in line with this, we focus on liquidity rather than equity.

[18] This calculation is based on the mean bank according to the *Exposure* measure.

models in column (3) and (4), for the Z-Score and MES, respectively. The added holding company controls are size measured as the logarithm of the assets, ROA, and leverage. The results in these models show similar results: the sign and significance of variables of interest remain unchanged, while both triple interaction estimates increase in absolute value. Among the added controls, only the holding ROA shows to be significantly related to the bank Z-Score. This variable enters with a negative sign. Thus, higher holding return is related to a higher risk of the subsidiary, consistent with the return-risk trade-off.

4.1.4.2 Spillover effects to other banks in the group

We now study whether unaffected banks that are part of a holding company with at least one affected bank display an increase in insolvency or systemic risk. It has been argued that cross-market spillover effects exist in the lending of banks operating in multiple banks (e.g., Berrospide, et al. 2016). These spillovers are likely to have an impact on bank risk. Furthermore, unaffected banks can also be affected by market reactions to perceived deterioration of implicit guarantees from the parent. This perception could also have an effect on their stock price volatility. To examine whether this is the case, we define a dummy variable *Group exposed* which equals 1 if there is at least one other bank in the same holding that is affected, and interact this variable with the *Exposure* measure. In particular, we estimate the following model for holding-company banks only:

$$\begin{aligned} Risk_{it} = \alpha_0 + \sum_i \alpha_{1,i} d_i + \alpha_2 Post_t + \beta_1 Exposure_i * Post_t + \beta_2 Group\ Exposed_i * Post_t \\ + \beta_3 Exposure_i * Post_t * Group\ Exposed_i + \epsilon_{it}. \end{aligned} \quad (5)$$

If an unaffected bank in an affected holding suffers spillover effects from other banks in the holding, we should observe a significant effect on β_2. Table 8 presents the results for these models. The insignificant coefficients of the interaction term between *Post* and *Exposure* show that there is no increase in risk for treated holding company banks, consistent with the previous section. But more importantly, we do not find a significant effect on the risk of unaffected banks in affected holdings, as suggested by the coefficients of the interaction term of the *Group exposed* and *Post* dummies, which are insignificant in both individual and systemic risk models.

The evidence in this section thus suggests two main findings: that the liquidity of the holding company plays a role in shaping the resiliency of holding-company banks; and that there is no evidence of increased risk for unaffected banks in the holding.

4.2 Holding company affiliation and stock returns

We have shown that holding company banks are more resilient to negative shocks than independent banks. Moreover, we have found that this resiliency is positively related to the holding's liquidity, consistent with internal capital markets playing a role in shaping bank stability. In this section, we exploit the higher frequency of market data and study the market reaction during the days following the shock, but more importantly, we examine whether the market distinguishes between independent and holding-company banks in its reaction. To this end, we perform an event study and measure changes in shareholder value resulting from the negative shock, while examining whether this valuation relates to holding affiliation.

4.2.1 Cumulative abnormal returns

We use the standard event study methodology (Brown and Warner, 1985) to estimate a market model computing banks' abnormal returns,

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{Mt}\right), \tag{6}$$

where R_{it} is the daily stock return of bank i on day t, and the R_{Mt} is the daily return of the market index, S&P 500. $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the intercept and slope coefficients of the estimated OLS market model. Following Brown and Warner (1985), we estimate this model including a maximum of 250 trading days, and we restrict the sample to banks that have at least 200 non-missing observations in this period. We estimate this model over the days between the 290^{th} and the 40^{th} day prior to the first hurricane's landfall. For each event (hurricane), we compute cumulative excess returns (CAR) over several time windows. We then aggregate the events to assess the market reaction over the whole period. Our final sample contains 87 banks (49 independent banks and 38 holding company banks). Summary statistics for the CARs are provided in Table 9. This table shows the statistics for the aggregated CARs for 1, 2, 10 and 15 days after the shock over the three hurricanes. As expected, Table 9 indicates that on average, the market views untreated banks more favorably than treated banks across all categories and time windows, as evidenced by the positive and often large standardized differences in panels A, B and C. However, treated independent banks have more negative CARs than treated holding company banks over the 2-day and 10-day time windows (-0.16 versus -0.12 for the 2-day window, and -0.28 vs. -0.21 for the 15-day window).

We conduct a multivariate cross-sectional analysis of the CARs. In particular, we estimate the following OLS model with robust standard errors:

$$CAR_i = \alpha + Exposure_i + Independent_i + Exposure_i * Independent_i + \sum_k \gamma_k X_{k,i} + \epsilon_i, \quad (7)$$

where CAR_i is the aggregated CAR of bank i over the three events. Following the literature (see e.g. Harvey et al., 2004) we include several controls $X_{k,i}$ that may affect a bank's CAR. These controls are bank size measured as *Log(assets)*, the *Book to market* ratio, *Leverage* and ROA. $Exposure_i$ and $Independent_i$ are respectively the treatment variable and independent bank dummy variable defined in the previous section.

In the previous section, we found evidence consistent with internal capital markets shaping holding company banks' higher stability. The expectation of within-holding capital transfers should affect banks' CARs in the days following the shock. In particular, we should observe a negative effect on CARs of affected independent banks and a positive effect on affected holding-company banks if the markets perceive the potential capital injection as value-enhancing. If instead, the market perceives potential capital injections from the parent as inefficient cross-subsidies, which obstruct efficient investment allocation within the holding, there should be a reduction in value: we should observe CARs of affected holding-company subsidiaries to be negatively affected after the shock. Such inefficient transfers can arise, for instance, due to agency problems between the shareholders, the CEO, and division managers, leading to division rent-seeking behavior and over-investment in poor projects, thus subsidizing weaker banks at the expense of profitable ones (Scharfstein and Stein, 2000).[19]

4.2.2 Results

The results of this study are presented in Table 10. The dependent variables in these models are the aggregated CARs over the different windows (1, 2, 10 and 15 days). The results in this table are in line with the results found in the previous section. There is a negative and statistically significant effect on affected independent banks' CARs after the shock and a positive and statistically significant effect on affected holding- company banks over all time windows. Hit independent banks thus experienced a reduction in

[19] Campello (2002) finds evidence of inefficient cross-subsidization within small bank holding companies.

value, while affected holding company banks experienced an increase in value after the shock. The positive effect on affected holding company banks suggests that the potential holding company dynamics of internal capital markets are perceived by the market as positive rather than as an inefficient subsidy to poor investments. The effects also suggest economic significance. Based on the estimates in column (4), one standard deviation increase in a holding-company bank's exposure increases the aggregated 15 days CAR over the three events by 0.44, whereas affected independent banks decrease their CAR by 0.02. These effects are significant considering that the mean of the 15-day CAR is -0.25.

Among the other control variables, bank size is negatively and statistically significantly related to bank CAR, consistent with larger banks being safer and hence commanding lower required returns. The banks' book-to-market ratio is positively and statistically significantly related to their CAR. This could be explained by the lower growth opportunities at banks that increase their required returns.

Next, we study the effect of shareholder valuation on unaffected banks in the holding. In the previous section, we did not find any risk spillovers from affected to unaffected banks in the same holding. The absence of a statistically significant effect could be due to the lower (quarterly) frequency of the data in our previous models; if this effect emerges only in the very short term, we will not observe any effect on longer-term measures. Thus, we now study whether there is an effect on unaffected banks' CARs in the days following the shock. If the market expects that the potential reallocation of resources towards hit banks could reduce guarantees and resources available to unaffected banks, we should observe a negative effect on their CARs in the days after a hurricane.

As in the previous section, we estimate this model only for holding company banks and include an interaction term with the dummy variable *Group exposed* which, as in the previous section, equals one if there is at least one other treated bank in the same group. The results of these models are displayed in Table 11. Results in this table show that affected banks increase their CARs after the shock, both when they are the only affected bank or when there is another affected bank in the group (the former effect is significant after 10 days only), as suggested by the single term *Exposure* and by the interaction term with *Group exposed*. This is consistent with the results found in Table 10 for holding-company banks. Interestingly, there is also a negative and statistically significant effect on the CARs of banks that belong to an affected group but were not affected themselves. This evidence suggests that the market expects a negative effect on such unaffected banks; this could be because of the expectation of moving away resources or reduced support from the parent. This effect is also economically significant. Based on the coefficient of the single term *Group exposed* in the fourth column of this table, we have that an unaffected bank in an exposed group decreases its aggregated CAR over 15 days by 0.91, which is significant considering that the mean of this variable is -0.25.

Taken together, the evidence in this section is consistent with affected holding-company banks performing better than independent banks after the shock. The positive stock market valuation of holding-company banks after the shock suggests that potential holding company dynamics are perceived as value-enhancing by the market. In addition, the negative effect on stock returns of unaffected banks in affected holdings is consistent with market value deterioration as a result of a perceived reduction in the support form the parent or resources available for these banks.

5 Conclusions

The literature on holding-company banks has discussed the benefits and costs of affiliation with a bank holding company on bank performance. On the one hand, holding-company banks can enjoy the support of their parents when overcoming adverse shocks. This is performed either directly, via resource transfers, or indirectly, via implicit guarantees perceived by the market. On the other hand, holding-company subsidiaries could also suffer from negative spillover effects from other banks in the holding when the latter become affected, or when the market's perception of the holding deteriorates. We revisit this discussion using an exogenous shock to bank balance sheets and higher-frequency market data to study the net effect of holding company affiliation on bank performance.

We show that holding-company banks are more stable than independent banks when affected by a negative shock. They display lower systemic risk levels as measured by the MES and SRISK metrics, and lower individual risk levels, as measured by market Z-Scores. Furthermore, we show evidence that the liquidity of the holding plays a role in shaping bank resiliency, consistent with an internal capital market story. Furthermore, the stock market valuation after the shock also differs for holding-company banks versus independent banks; stock market value increases for affected holding-company banks, but decreases for independent banks after the shock. This suggests that potential holding company dynamics after the shock are perceived as beneficial by the market. In addition, we also show that shareholder value decreases for unaffected banks in affected holdings. We argue that this is consistent with a perceived decrease in parental support or resources available to such banks.

This paper complements the literature on multibank holding companies. The closest papers to ours have studied the relationship between holding affiliation and CAMEL ratings (Ashcraft, 2008), and holding company affiliation and risk-based capital (Lambert et al., 2018). We complement this literature by examining banks' market outcomes. The study of market-based outcomes allows us to test additional effects of holding company affiliation, not studied in this literature, such as banks' perceived implicit guarantees and inefficient cross-subsidization. This study sheds light on the holding's role in restoring stability and the potential dynamics behind it.

Our findings are also important in view of the ongoing discussion of bank holding company regulation after the 2008 crisis, including the Dodd-Frank Act and the recent financial deregulation.[20] The crisis revealed that bank holding companies had accumulated more risks than independent banks, and accounted for 572 out of the 709 entities receiving TARP aid. This could be either because the holding form of organization is riskier, or because holdings take seriously their commitment to support troubled subsidiaries through implicit guarantees or internal capital markets. This paper suggests that bank holding companies may play an underappreciated role in stabilizing the systemic risk of their affiliates through these channels, and shows evidence that the market values parental support in the immediate aftermath of a shock. If holdings allocate internal liquidity efficiently and avoid inefficient cross-subsidization – something supported by our event study – then disbursing government liquidity through multibank holdings and letting it trickle down to those subsidiaries that need it may have been optimal despite the too-big-to-fail nature of some holdings. The fact that TARP aid was successful in reducing systemic risk (Berger et al., 2016) lends further credibility to this view.

To the best of our knowledge, this is the first paper to study how holding company affiliation affects bank risk measures. The previous literature has focused on the effects of bank characteristics (e.g. Laeven et al., 2016, De Jonghe 2010), banking system competition levels (e.g. Beck, 2008, Anginer et al., 2014), and country characteristics (e.g. Anginer et al., 2014). Our paper's empirical strategy allows us to compare how independent and holding-company banks react to the same exogenous shock, and how their risks are affected.

[20]Title VI of the Dodd-Frank Act introduced additional restrictions on holding companies in terms of capitalization, management, lending limits, and mergers and acquisitions. Some of them were relaxed by the Economic Growth, Regulatory Relief and Consumer Protection Act of May 2018.

References

[1] Acharya, V. V., Engle, R. F. and Richardson, M. (2012). Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risks. *American Economic Review 102, pp. 59–64.*

[2] Acharya, V. V., Hasan, I, and Saunders, A. (2006). Should Banks Be Diversified? Evidence from Individual Bank Loan Portfolios. *Journal of Business 79(3), pp. 1355–1412.*

[3] Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring Systemic Risk. *Review of Financial Studies, 30(1) pp. 2–47.*

[4] Almeida, H., Kim, C., and Kim, H. (2015). Internal Capital Markets in Business Groups: Evidence from the Asian Financial Crisis. *Journal of Finance 70, pp. 2539–2586.*

[5] Anginer, D., Demirguc-Kunt, A., and Zhu, M. (2014). How does Competition Affect Bank Systemic Risk? *Journal of Financial Intermediation, 23(1), pp.1–26*

[6] Angrist, J., and Pischke, J. S. (2009). Mostly Harmless Econometrics. *Princeton University Press.*

[7] Ashcraft, A. (2008). Are Bank Holding Companies a Source of Strength to Their Banking Subsidiaries?. *Journal of Money, Credit and Banking 40, pp. 273–294.*

[8] Beck, T. (2008). Bank Competition and Financial Stability: Friends or Foes? The World Bank, Policy Research Working Paper 4656.

[9] Bena, J. and Ortiz-Molina, H. (2013). Pyramidal ownership and the creation of new firms. *Journal of Financial Economics 108, pp. 798–821.*

[10] Berger, A., Davies S., and Flannery, M. (1998). Comparing Market and Supervisory Assessment of Bank Performance: Who Knows What When? Federal Reserve Board of Governors Finance and Economics Discussion Series, Working paper 1998-32.

[11] Berger, A., Roman, R., and Sedunov, J. (2016). Do Bank Bailouts Reduce or Increase Systemic Risk? The Effects of TARP on Financial System Stability. Federal Reserve Bank of Kansas City Research Working Paper 16-08, `https://dx.doi.org/10.18651/RWP2016-08`.

[12] Berrospide, J., Black, L., and Keeton, W. (2016). The Cross-Market Spillover of Economic Shocks through Multimarket Banks. *Journal of Money, Credit and Banking 48, pp. 957–988.*

[13] Blanchard, O. Lopez-de-Silanes, F., and Shleifer, A. (1994). What Do Firms Do with Cash Windfalls? *Journal of Financial Economics, 36(3)*, pp. 337–360

[14] Brownlees, C., and Engle, R. (2017). SRISK: a conditional capital shortfall measure of systemic risk. *Review of Financial Studies 30(1), pp. 48–79.*

[15] Brunnermeier, M., Dong, G., and Palia, D. (2012). Banks Non-Interest Income and Systemic Risk. *AFA 2012 Chicago Meetings Paper.*

[16] Byun, H., Choi, S., Hwang, L., and Kim, R. (2013). Business group affiliation, ownership structure, and the cost of debt. *Journal of Corporate Finance 23, pp. 311–331.*

[17] Campello, M. (2002). Internal Capital Markets in Financial Conglomerates: Evidence from Small Bank Responses to Monetary Policy. *Journal of Finance, 57(6), pp. 2773–2805.*

[18] Chavaz, M. (2016). Disintegrating Credit Markets: Diversification, Securitization, and Lending in a Recovery. *Staff Working Paper No. 617, Bank of England.*

[19] Chong, B. (1991). Interstate Banking on Commercial Banks' Risk and Profitability. *Review of Economics and Statistics, 73, pp. 78–84.*

[20] Cole, R., and Gunther, J. (1998). Predicting Bank Failures: A Comparison of On- and Off-Site Monitoring Systems. *Journal of Financial Services Research 13, pp. 103–117.*

[21] Cortés, K. and Strahan, P. (2017). Tracing Out Capital Flows: How Financially Integrated Banks Respond to Natural Disasters. *Journal of Financial Economics, 125(1), pp. 182–199.*

[22] De Jonghe, O. (2010). Back to the Basics in Banking? A Micro-analysis of Banking System Stability. *Journal of Financial Intermediation, 19(3), pp. 387–417.*

[23] Demsetz, R. and Strahan, P. (1997). Diversification, Size, and Risk at Bank Holding Companies. *Journal of Money, Credit and Banking, 29(3), pp. 300–313.*

[24] Deng, E., Elyasiani, E. (2008). Geographic Diversification, Bank Holding Company Value, and Risk. *Journal of Money, Credit and Banking, 40(6), pp. 1217–1238.*

[25] Federal Deposit Insurance Corporation (2005). FDIC Outlook, Winter 2005.

[26] Federal Financial Institution Examination Council. (2005). Guidance for Financial Institutions in Response to Hurricanes Katrina and Rita. `https://www.ffiec.gov/katrina.htm`. Accessed on March 7, 2018.

[27] Ferris, S., Kim, K., and Kitsabunnarat, P. (2003) The costs (and benefits?) of diversified business groups: The case of Korean chaebols.*Journal of Banking and Finance 27, pp. 251–273.*

[28] Garmaise, M., and Moskowitz, T. (2009). Catastrophic Risk and Credit Markets, *The Journal of Finance 64, pp. 657–707.*

[29] Gilbert, R. (1991). Do Bank Holding Companies Act as a Source of Strength for Their Bank Subsidiaries? *Economic Review, Federal Reserve Bank of St. Louis, January/February, pp. 3 –18.*

[30] Goetz, M., Laeven, L., Levine, R. (2016). Does the Geographic Expansion of Banks Reduce Risk? *Journal of Financial Economics 120 (2016), pp. 346-362.*

[31] Gopalan, R., Nanda, V., and Seru, A. (2007). Affiliated firms and financial support: Evidence from Indian business groups. *Journal of Financial Economics 86, pp. 759–795.*

[32] Harvey, C., Lins, K., and Roper, A. (2004). The effect of capital structure when expected agency costs are extreme. *Journal of Financial Economics 74*, pp. 3–30.

[33] Houston, J., James, C., and David, M. (1997). Capital Market Frictions and the Role of Internal Capital Markets in Banking. *Journal of Financial Economics 46, pp. 135–64.*

[34] Hughes, J., Lang, W., Mester, L., and Moon, C. (1996). Banking under Interstate Branching. *Journal of Money, Credit and Banking 28, pp. 1045 – 1071.*

[35] Jaffee, D., and Russell, T. (1997). Catastrophe insurance, capital markets, and uninsurable risks. *Journal of Risk and Insurance, 64(2)*, pp. 205230.

[36] Klomp, J. (2014). Financial Fragility and Natural Disasters: An Empirical Analysis. *Journal of Financial Stability, pp. 180–192.*

[37] Laeven, L., Ratnovski, L., and Tong, H. (2016). Bank Size, Capital, and Systemic Risk: Some International Evidence. *Journal of Banking and Finance, 69(1), pp. 25–34.*

[38] Lambert, C., Noth, F., and Schüwer, U. (2018) How do Banks React to Catastrophic Events? Evidence from Hurricane Katrina. *Review of Finance, forthcoming.*

[39] Larraín, B., Sertsios, G., and Urzúa, F. (2018) The Effects of Losing Business Group Affiliation. *Review of Financial Studies, forthcoming*

[40] Lepetit, L., Nys, E., Rous, P., and Tarazi, A. (2008) Bank Income Structure and Risk: An Empirical Analysis of European Banks. *Journal of Banking and Finance 32, pp.1452–1467.*

[41] National Hurricane Center. (2018). Costliest US Tropical Cyclones Tables (updated). `https://www.nhc.noaa.gov/news/UpdatedCostliest.pdf`

[42] Noth, F., and Schüwer, U. (2017). Natural Disasters and Bank Stability: Evidence from the US Financial System. *SAFE Working Paper No. 167*

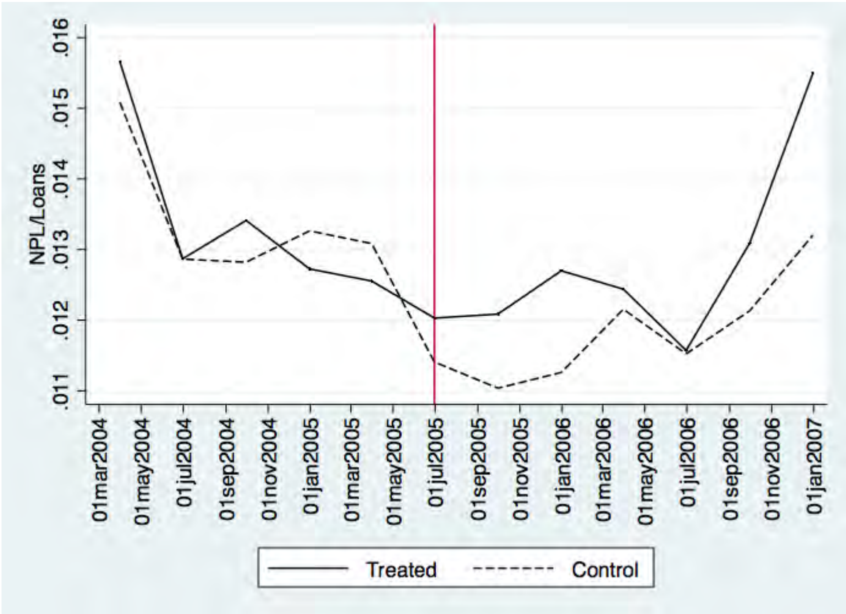
[43] Petersen, M. and Rajan, R. (2002). Does Distance Still Matter? The Information Revolution in Small Business Lending. *Journal of Finance 57(6), pp. 2533–2570.*

[44] Scharfstein, D., and Stein, J. (2000). The dark side of internal capital markets: divisional rent-seeking and inefficient investment. *Journal of Finance 55(6), pp. 2537–2564.*

[45] Shin, H. and Park, Y. (1999). Financing constraints and internal capital markets: Evidence from Korean chaebols. *Journal of Corporate Finance 5, pp. 169–191.*

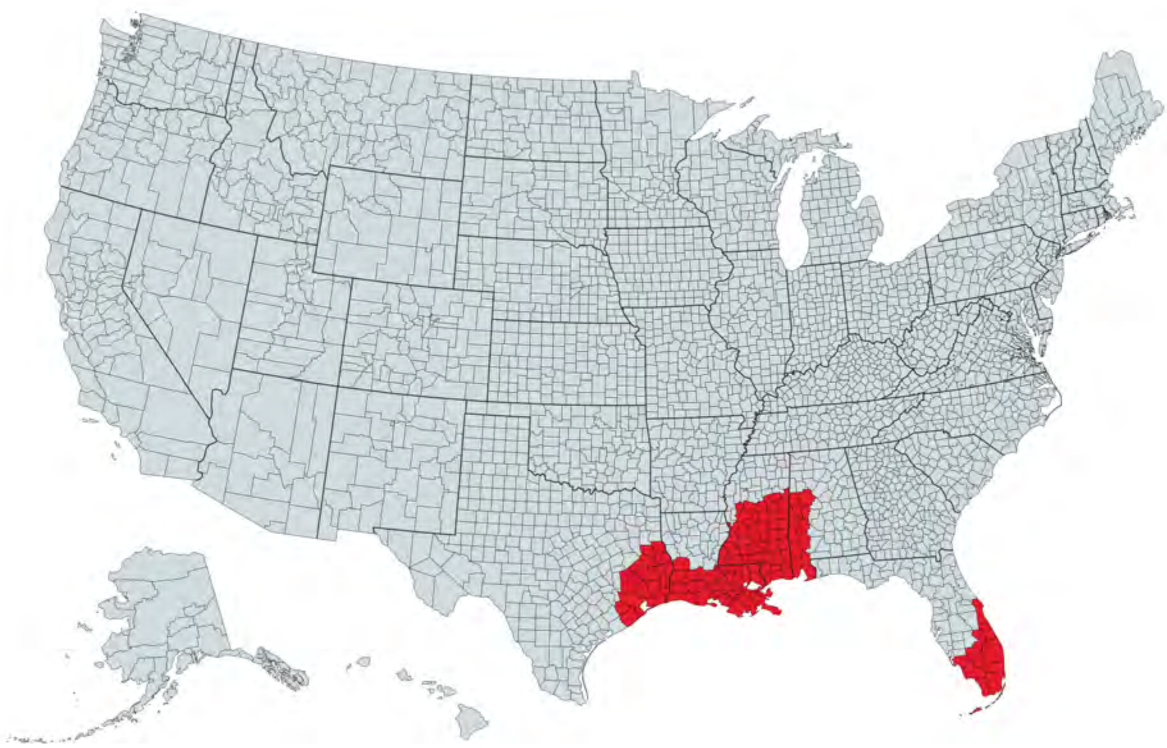
Figures

Figure 1. Evolution of Nonperforming Loans



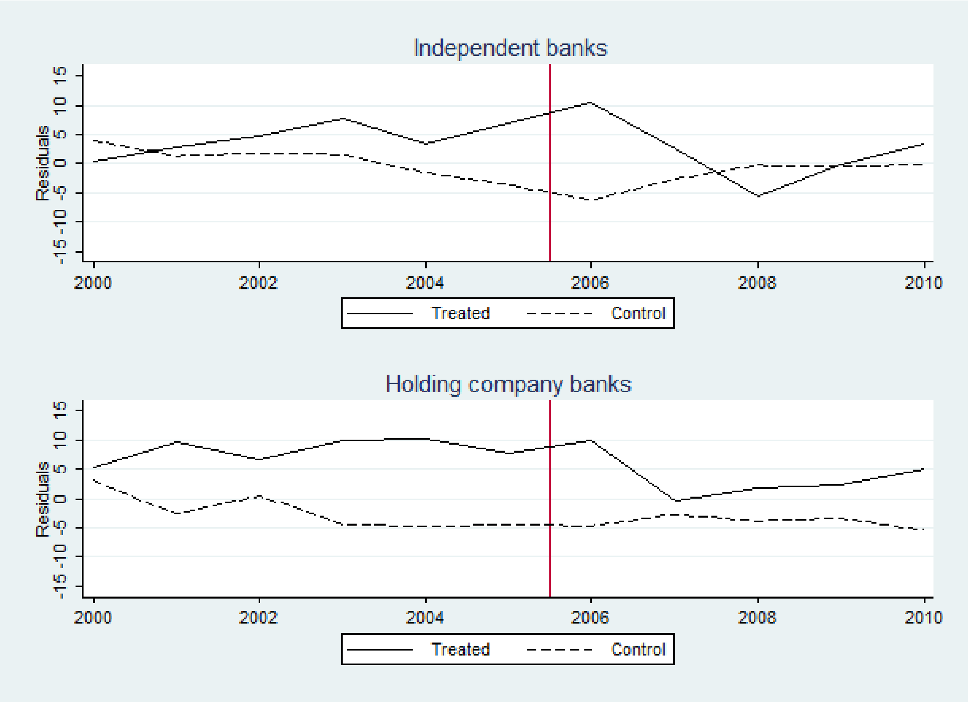
Evolution of nonperforming loans as a share of total loans for treated and control banks over time. A bank is defined as treated if it had positive mortgage lending to a affected county during 2002-04.

Figure 2. US Counties Affected by the 2005 Atlantic Hurricane Season



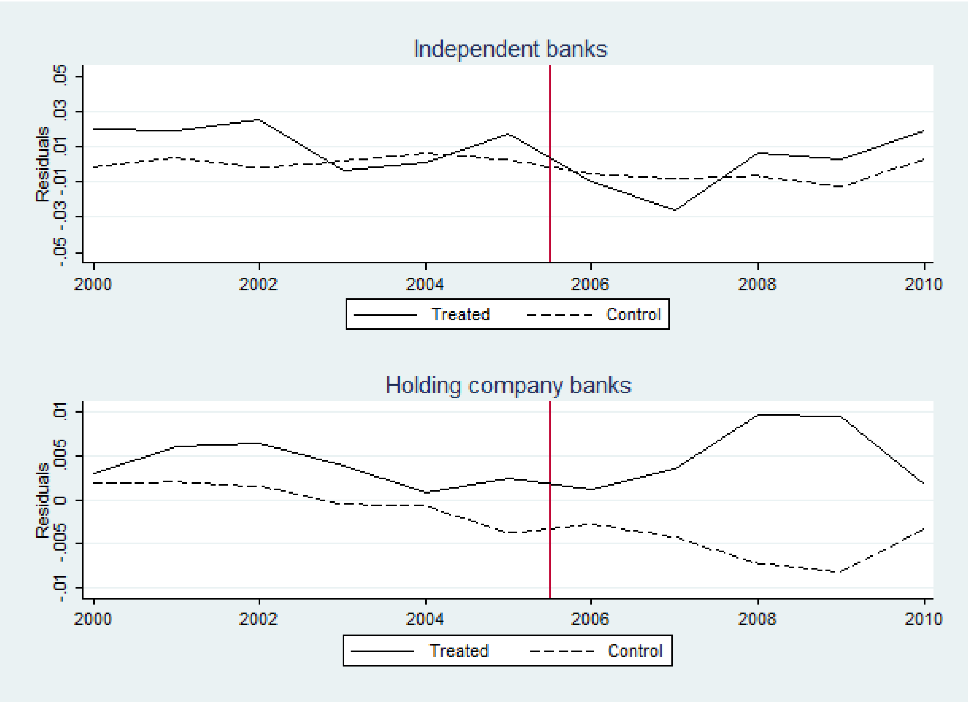
Counties affected by hurricanes Katrina, Rita and Wilma (in red), and unaffected counties (in grey). A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04.

Figure 3. Average Z-Score Residuals over Time



The figure shows the average residuals by year and treatment group of a regression of Z-Score on bank and state-year fixed effects. The vertical line indicates the quarter when hurricanes Katrina, Rita and Wilma hit the US Gulf coast region. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04.

Figure 4. Average MES Residuals over Time



The figure shows the average residuals by year and treatment group of a regression of MES on bank and state-year fixed effects. The vertical line indicates the quarter when hurricanes Katrina, Rita and Wilma hit the US Gulf coast region. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04 and defined as independent if the bank does not have a parent bank according to Bloomberg.

Tables

Table 1: Distribution of Treated and Control Banks

	All banks	Independent banks	Holding company banks
Control	3,982	2,798	1,184
Treated	1,448	903	545
Total	5,430	3,701	1,729

Number of bank-quarter observations for our sample (bank-years from 2002 to 2007) across treated and control groups, and independent versus holding-company banks. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04.

Table 2: Summary Statistics

	Full sample					Matched sample				
	Control		Treated			Control		Treated		
	Mean	Std. Dev.	Mean	Std. Dev.	Std. Diff	Mean	Std. Dev.	Mean	Std. Dev.	Std. Diff
Panel A: Full sample										
Exposure	0	0	0.094	0.243	-0.545	0	0	0.156	0.327	-0.672
Z-Score	55.98	33.95	64.47	27.99	-0.273	57.81	34.49	56.75	28.37	0.033
MES	0.00035	0.031	0.009	0.019	-0.350	-0.001	0.026	0.001	0.020	-0.085
Log(assets)	12.25	1.14	13.98	1.80	-1.152	12.53	1.08	12.77	0.88	-0.239
Leverage	0.894	0.040	0.907	0.019	-0.422	0.901	0.035	0.906	0.015	-0.188
ROA	0.004	0.007	0.006	0.005	-0.383	0.005	0.006	0.005	0.006	0.027
Non-interest/Income	0.806	0.906	1.265	1.135	-0.448	0.833	0.925	1.179	1.348	-0.299
Loan growth	1.056	0.084	1.042	0.065	0.195	1.044	0.075	1.059	0.073	-0.202
Panel B: Independent banks										
Exposure	0	0	0.103	0.263	-0.554	0	0	0.129	0.301	-0.606
Z-Score	56.19	35.49	61.89	28.60	-0.177	58.60	35.41	56.97	30.45	0.049
MES	-0.0002	0.032	0.006	0.021	-0.234	-0.0007	0.026	0.000	0.021	-0.052
Log(assets)	12.20	1.04	13.48	1.53	-0.975	12.60	1.04	12.86	0.817	-0.272
Leverage	0.896	0.039	0.905	0.020	-0.318	0.903	0.031	0.907	0.013	-0.146
ROA	0.004	0.007	0.006	0.005	-0.383	0.005	0.006	0.005	0.005	-0.047
Non-interest/Income	0.869	0.975	1.241	1.194	-0.341	0.875	0.949	1.078	1.210	-0.187
Loan growth	1.049	0.076	1.041	0.066	0.123	1.035	0.064	1.055	0.071	-0.290
Panel C: Holding-company banks										
Exposure	0	0	0.079	0.207	-0.539	0	0	0.295	0.416	-1.002
Z-Score	55.55	30.58	67.56	26.97	-0.416	50.11	22.75	55.75	16.22	-0.285
MES	0.0013	0.031	0.013	0.016	-0.479	-0.004	0.024	0.003	0.013	-0.348
Log(assets)	12.37	1.34	14.81	1.90	-1.482	11.82	1.20	12.28	1.02	-0.414
Leverage	0.890	0.043	0.910	0.017	-0.624	0.876	0.057	0.901	0.021	-0.570
ROA	0.003	0.009	0.006	0.006	-0.399	0.000	0.009	0.000	0.008	-0.001
Non-interest/Income	0.649	0.680	1.304	1.032	-0.750	0.424	0.473	1.713	1.841	-0.959
Loan growth	1.074	0.100	1.043	0.065	0.365	1.138	0.110	1.083	0.077	0.580

Summary statistics for the pre-shock period across three categories. The tables display covariate means and standard deviations for treated and control banks in Panel A; for treated and control independent banks in Panel B; and for treated and control holding-company banks in Panel C. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04 and defined as independent if the bank does not have a parent bank according to Bloomberg. The full samples are presented on the left side of each panel and the matched samples on the right. The normalized difference in means are also displayed. Definitions and sources of control variables are listed in Appendix A.

Table 3: Bank Risk

	Z-Score (1)	MES (2)	Z-Score (3)	MES (4)
Post	9.978***	0.00173	8.885***	0.00352*
	(1.602)	(0.00121)	(2.219)	(0.00195)
Post*Exposure	-15.96	0.0157	27.67	-0.0335*
	(11.65)	(0.0130)	(16.82)	(0.0177)
Post*Independent			1.483	-0.00265
			(3.129)	(0.00251)
Post*Exposure*Independent			-47.59**	0.0539**
			(20.11)	(0.0232)
Bank FE	Yes	Yes	Yes	Yes
Observations	3,082	2,338	3,082	2,338
R-squared	0.027	0.004	0.028	0.006

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: Robustness

	Placebo test		Bank controls		Matched sample		County-Year FE	
	Z-Score	MES	Z-Score	MES	Z-Score	MES	Z-Score	MES
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post placebo	12.84***	0.000822						
	(2.685)	(0.00248)						
Post placebo*Exposure	32.39	-0.0232						
	(24.15)	(0.0224)						
Post placebo*Independent	1.031	-0.00229						
	(3.627)	(0.00286)						
Post placebo*Independent*Exposure	-47.61	0.0450						
	(30.72)	(0.0335)						
Post			6.471**	4.73e-05	3.087	0.00525	-2.620	-0.000538
			(2.844)	(0.00213)	(3.331)	(0.00460)	(3.565)	(0.00310)
Post*Exposure			37.70*	-0.0235	61.20***	-0.00485	61.92**	-0.111*
			(19.58)	(0.0161)	(19.79)	(0.0280)	(26.36)	(0.0651)
Post placebo*Independent			2.337	-0.00254	6.617	-0.00358	7.689*	-0.00337
			(3.280)	(0.00253)	(4.418)	(0.00522)	(4.496)	(0.00359)
Post*Independent*Exposure			-59.22***	0.0406**	-50.31**	0.0673**	-73.42***	0.121*
			(22.27)	(0.0194)	(20.92)	(0.0284)	(27.43)	(0.0651)
Log(assets)			3.392	0.00809***				
			(3.710)	(0.00289)				
Leverage			18.68	-0.0499				
			(64.28)	(0.0580)				
ROA			-20.49	-0.0546				
			(178.2)	(0.136)				
Non-interest/Income			0.207	-0.000710				
			(1.067)	(0.00127)				
Loan growth			-2.936	-0.0116				
			(12.45)	(0.0119)				
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Year FE	No	No	No	No	No	No	Yes	Yes
Observations	2,253	1,681	2,931	2,225	1,099	810	3,082	2,338
R-squared	0.048	0.003	0.024	0.013	0.025	0.025	0.354	0.363

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. Definitions and sources of control variables are listed in Appendix A. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 5: Geographic Diversification

	Z-Score	MES	Z-Score	MES
	(1)	(2)	(3)	(4)
Post	8.844***	0.00406	7.797	0.00672
	(3.258)	(0.00365)	(4.740)	(0.00465)
Post*Exposure	-47.39***	0.0479*	11.40	-0.00274
	(17.35)	(0.0257)	(26.89)	(0.0230)
HHI_{div}	2.526	0.00552	2.558	0.00581
	(5.766)	(0.00733)	(5.761)	(0.00735)
Exposure*HHI_{div}	-169.6***	-0.0634	-151.1***	-0.0764*
	(37.15)	(0.0560)	(45.75)	(0.0458)
Post*HHI_{div}	1.144	-0.00353	1.265	-0.00451
	(4.949)	(0.00467)	(5.509)	(0.00500)
Post*Exposure*HHI_{div}	38.93*	-0.0423	21.12	-0.0288
	(22.65)	(0.0344)	(28.78)	(0.0240)
Post*Independent			1.273	-0.00311
			(3.448)	(0.00272)
Post*Independent*Exposure			-49.29***	0.0445***
			(18.89)	(0.0158)
Bank FE	Yes	Yes	Yes	Yes
Observations	2,936	2,266	2,936	2,266
R-squared	0.029	0.009	0.029	0.011

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. HHI_{div} is the sum of the squared share of a holding lending in each county over its total lending using data of the year 2004. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 6: Risk Based Capital Ratios

	Z-Score	MES	Z-Score	MES
	(1)	(2)	(3)	(4)
Post	0.625	0.00460*	0.117	0.00555**
	(4.344)	(0.00239)	(4.500)	(0.00278)
Post*Exposure	-13.34	0.308	63.14	0.252
	(127.2)	(0.255)	(124.2)	(0.256)
Capital ratio	-26.59*	-0.0592***	-26.82*	-0.0580***
	(16.02)	(0.0193)	(16.11)	(0.0192)
Capital ratio*Exposure	92.72	2.960	348.5	2.777
	(1,000)	(2.131)	(975.9)	(2.130)
Post*Capital ratio	66.48**	-0.0236	68.00**	-0.0213
	(30.61)	(0.0171)	(31.06)	(0.0163)
Post*Capital ratio*Exposure	-7.187	-2.578	-245.4	-2.406
	(1,052)	(2.189)	(1,031)	(2.200)
Post*Independent			0.199	-0.00187
			(3.175)	(0.00245)
Post*Independent*Exposure			-53.52***	0.0398**
			(19.50)	(0.0177)
Bank FEs	Yes	Yes	Yes	Yes
Observations	3,082	2,338	3,082	2,338
R-squared	0.032	0.013	0.032	0.014

This table presents the results of additional regressions studying the effects of the hurricane season on the banks' risks. The regressions now include the capital ratio as a control and its interaction with the *Post* dummy to capture any differential effect of the capital ratio's response to the shock on bank risk. The dependent variables are MES and $Z-Score$. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. Definitions and sources of control variables are listed in Appendix A. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Holding-Company Banks and the Role of the Holding

	Z-Score	MES	Z-Score	MES
	(1)	(2)	(3)	(4)
Post	4.870	0.00489	0.773	0.00496
	(6.297)	(0.00549)	(6.927)	(0.00493)
Post*Exposure	-404.5**	0.380**	-464.2*	0.404**
	(198.6)	(0.161)	(231.1)	(0.178)
Liquid/TA$_{Holding}$	-257.5**	-0.0598	-232.2*	-0.0640
	(108.6)	(0.126)	(118.7)	(0.133)
Exposure*Liquid/TA$_{Holding}$	-3,657	1.330	-3,850*	1.522
	(2,251)	(2.797)	(2,141)	(2.840)
Post*Liquid/TA$_{Holding}$	75.98	-0.00942	151.6	-0.0240
	(196.4)	(0.174)	(201.9)	(0.164)
Post*Exposure*Liquid/TA$_{Holding}$	16,036**	-16.03**	18,556**	-17.07**
	(7,598)	(6.179)	(8,850)	(6.903)
Log(assets)$_{Holding}$			10.83*	-0.000212
			(5.778)	(0.00601)
Leverage$_{Holding}$			93.13	-0.0577
			(152.0)	(0.150)
ROA$_{Holding}$			-866.8***	0.452
			(189.6)	(0.293)
Bank FE	Yes	Yes	Yes	Yes
Observations	797	691	797	691
R-squared	0.049	0.018	0.065	0.024

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. $Liquid/TA_{Holding}$ corresponds to the holding cash and balances from depository institutions as a share of assets and $Equity/TA_{Holding}$ corresponds to the holding equity over assets. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Spillover Effects Within Holdings

	Z-Score (1)	MES (2)
Post	9.276***	0.00375*
	(2.405)	(0.00209)
Post*Group exposed	-5.690	-0.00230
	(3.434)	(0.00488)
Post*Exposure	27.44	-0.0294*
	(17.50)	(0.0173)
Post*Exposure*Group exposed	53.43	-0.0187
	(36.75)	(0.0612)
Bank FE	Yes	Yes
Observations	840	617
R-squared	0.021	0.021

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Group exposed* equals one for unaffected banks that are part of a group where at least one bank is affected. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank-level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9: Summary Statistics of Cumulative Abnormal Returns

	Control		Treated		
	Mean	Std. Dev.	Mean	Std. Dev.	Std. Diff
Panel A: Full sample					
CAR 1 day	-.0095	.4901	-.2418	.3865	0.5263
CAR 2 days	-.0365	.4307	-.1429	.3865	0.2601
CAR 10 days	-.0371	.8441	-.2508	.6574	0.2825
CAR 15 days	.0045	.8950	-.4048	.6307	0.5287
Panel B: Independent banks					
CAR 1 day	.0994	.4928	-.2382	.4650	0.7047
CAR 2 days	-.0009	.4548	-.1626	.4305	0.3651
CAR 10 days	-.0849	.7371	-.2843	.6501	0.2869
CAR 15 days	.0059	.7415	-.4056	.6227	0.6010
Panel C: Holding-company banks					
CAR 1 day	-.1991	.4312	-.2460	.2819	0.1287
CAR 2 days	-.0983	.3855	-.1199	.3389	0.0595
CAR 10 days	.0462	1.014	-.2117	.6825	0.2985
CAR 15 days	.0019	1.130	-.4040	.6580	0.4391

Summary statistics of cumulative abnormal returns (CAR) across three bank categories and four different time horizons (1, 2, 10 and 15 days post-shock). The table displays covariate means and standard deviations for treated and control banks in Panel A; for treated and control independent bank in Panel B; and for treated and control holding-company banks in Panel C. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04 and defined as independent if the bank does not have a parent bank according to Bloomberg. The normalized difference in means is displayed in the last column. Definitions and sources of control variables are listed in Appendix A.

Table 10: Cumulative Abnormal Returns

	CAR one day	CAR two days	CAR 10 days	CAR 15 days
	(1)	(2)	(3)	(4)
Exposure	1.703**	1.618**	3.676***	4.022***
	(0.786)	(0.722)	(1.299)	(1.132)
Independent	0.158*	0.0558	0.0596	0.211
	(0.0941)	(0.0988)	(0.185)	(0.166)
Independent*Exposure	-1.761*	-2.098**	-4.210***	-4.162***
	(0.937)	(0.884)	(1.364)	(1.282)
Log(assets)	-0.105***	-0.0443	-0.0438	-0.128***
	(0.0385)	(0.0352)	(0.0411)	(0.0403)
Book to market	0.00563***	-0.00155	-0.00153	0.0159***
	(0.00211)	(0.00196)	(0.00421)	(0.00443)
Leverage	0.404	-1.076	-4.004	-1.649
	(1.887)	(1.861)	(3.331)	(2.456)
ROA	4.232	5.518	-35.35	-29.55*
	(28.46)	(21.31)	(23.92)	(16.86)
Constant	0.785	1.408	4.272	3.012
	(1.575)	(1.691)	(3.051)	(2.243)
Observations	87	87	87	87
R-squared	0.161	0.051	0.093	0.211

This table presents the results of cross-sectional regressions studying the effects of the hurricane season on the banks' cumulative abnormal returns. The dependent variables are cumulative abnormal returns aggregated over 1, 2, 10 and 15 days after each event. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. *Log*(*assets*) denotes log assets, *Book to market* is the bank's book value to market value ratio, *Leverage* is the bank's leverage, and *ROA* is its return on assets. Market model parameters are estimated by OLS from $t = -290$ to $t = -40$, where $t = 0$ is the day of hurricane Katrina's landfall. The cross-sectional regressions are estimated by OLS with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 11: Cumulative Abnormal Returns: Unaffected Banks in Affected Holdings

	CAR one day	CAR two days	CAR 10 days	CAR 15 days
	(1)	(2)	(3)	(4)
Exposure	0.424	0.315	2.848*	3.162**
	(0.770)	(0.707)	(1.498)	(1.266)
Group exposed	-0.549***	-0.527***	-0.632**	-0.917***
	(0.147)	(0.125)	(0.276)	(0.267)
Group exposed*Exposure	12.09***	10.44***	12.21***	21.64***
	(2.350)	(1.894)	(4.024)	(3.715)
Book to market	0.00319	-0.00319	-0.00196	0.0159***
	(0.00202)	(0.00227)	(0.00462)	(0.00421)
Log(assets)	-0.0357	0.0190	-0.0562	-0.159*
	(0.0408)	(0.0463)	(0.0973)	(0.0843)
Leverage	0.453	1.753	2.954	0.713
	(2.318)	(2.379)	(5.419)	(3.796)
ROA	-36.90	-42.70	-37.48	-40.56
	(33.67)	(30.93)	(62.87)	(59.76)
Constant	0.188	-1.551	-1.776	1.460
	(2.124)	(2.088)	(4.916)	(3.428)
Observations	38	38	38	38
R-squared	0.277	0.214	0.120	0.293

This table presents the results of cross-sectional regressions studying the effects of the hurricane season on the cumulative abnormal returns of unaffected banks within affected holdings. The dependent variables are cumulative abnormal returns aggregated over 1, 2, 10 and 15 days after each event. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Group exposed* equals one for unaffected banks that are part of a group where at least one bank is affected. *Independent* equals one if the bank is independent. *Log(assets)* denotes log assets, *Book to market* is the bank's book value to market value ratio, *Leverage* is the bank's leverage, and *ROA* is its return on assets. Market model parameters are estimated by OLS from $t = -290$ to $t = -40$, where $t = 0$ is the day of hurricane Katrina's landfall. The cross-sectional regressions are estimated by OLS with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Appendix A: Variable Definitions

Variable	Definition	Source
Risk measures		
Z-Score	A bank's average return over the standard deviation of returns	Authors' calculation using stock price data from Bloomberg
MES	A bank's average return taken over the days scoring the 5% worst daily returns of the *banking sector* for each quarter	Authors' calculation using stock price data from Bloomberg
Cumulative abnormal returns		
CAR n days	Cumulative abnormal returns as defined in the model in section 4.2.1, eq. (6)	Authors' calculation using stock price data from Bloomberg
Treatment and multibank variables		
Exposure	Continuous variable denoting the share of mortgage loans extended by each bank to FEMA-designated disaster areas from 2002 to 2004	Authors' definition using HMDA data
Group exposed	Dummy equal to 1 for unaffected banks that are part of a holding where at least one bank is affected	Authors' definition using holding company affiliation data from Bloomberg
Post	Dummy equal to 1 from the third quarter of 2005 on	
Post-placebo	Dummy equal to 1 from the first quarter of 2005 on	
Independent	Dummy equal to 1 if the bank is not part of a holding company	Authors' definition using holding company affiliation data from Bloomberg
Bank controls		
Log(assets)	Logarithm of assets	US Call Reports
Leverage	Debt over assets	US Call Reports
ROA	Net income over assets	US Call Reports
Non-interest/Income	Non-interest income over total income	US Call Reports
Loan growth	Quarterly loan growth	US Call Reports

Appendix B: Matched Sample Holding Company Affiliation

	Z-Score	MES
	(1)	(2)
Post	8.375***	0.00418**
	(2.223)	(0.00197)
Post*Exposure	31.01*	-0.0377**
	(17.22)	(0.0180)
Post*Independent	1.688	-0.00178
	(3.611)	(0.00246)
Post*Exposure*Independent	-60.79***	0.0419**
	(17.60)	(0.0180)
Bank FE	Yes	Yes
Observations	2,108	1,656
R-squared	0.029	0.008

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended to FEMA-designated disaster areas by each bank during the pre-shock period. *Independent* equals one if the bank is independent. The sample period spans from 2002-2007. All regressions are estimated including bank fixed effects and robust standard errors clustered at the bank-level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Appendix C: Alternative Measure of Bank Risk

	SRISK	SRISK	SRISK
	(1)	(2)	(3)
Post	-0.000687*	-0.000427	-0.00110**
	(0.000348)	(0.000462)	(0.000527)
Post*Exposure	-0.00186	-0.0306**	-0.0277**
	(0.00251)	(0.0120)	(0.0106)
Post*Independent		-0.000201	-0.000118
		(0.000658)	(0.000593)
Post*Independent*Exposure		0.0311**	0.0274**
		(0.0120)	(0.0107)
Log(assets)			0.00180***
			(0.000630)
Leverage			-0.0141
			(0.0163)
ROA			7.89e-05
			(0.0137)
Non-interest/Income			-0.000103
			(0.000138)
Loan growth			0.000862
			(0.000633)
Observations	2,201	2,201	2,094
R-squared	0.031	0.074	0.111

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variable is bank's SRISK. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable that denotes the share of mortgage loans extended by each bank to FEMA-designated disaster areas during the pre-shock period. *Independent* equals one if the bank is independent. Definitions and sources of control variables are listed in Appendix A. The sample period spans from 2002-2007. All regressions are estimated with robust standard errors clustered at the bank-level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.