Holding Company Affiliation and Bank Stability: Evidence from the US Banking Sector

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Abstract

Is affiliation with a multibank holding company beneficial for bank stability? We revisit this question by examining the response of market-based risk measures of independent and multibank-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 stability. We also conduct an event study showing that markets perceive multibank-holding-company banks' dynamics after the shock as value-enhancing.

Keywords: Holding company banks; systemic risk; financial stability

JEL codes: G1, G2.

1 Introduction

The 2008 financial crisis has renewed interest in the main factors behind bank stability. One such factor may be holding company affiliation. The literature on non-financial holding companies shows that firms that are part of a holding differ from independent firms on several dimensions, including their capital structure (Larraín et al., 2019) and investments (Shin and Park, 1999). This literature has also widely studied the costs and benefits of internal capital markets operating within holding companies (e.g. Stein, 1997; Scharfstein and Stein, 2000). Compared to non-financial firms, bank holding companies are regulated much more strictly, and face specific requirements to serve as a source of strength for troubled subsidiaries by assisting them financially and managerially.[1] These requirements may influence incentives within bank holdings in a way different than for non-banks. For example, subsidiary moral hazard may be more pronounced for banks, or the 'source of strength' regulation may faciliate inefficient cross-subsidies. Holding-affiliated banks are already known to differ in their lending behavior (Houston et al., 1997), risk-based capital ratios (Lambert et al., 2018) and funding sources (Campello, 2002). Hence, the dynamics of holding company banks might be different.

Holding company affiliation can have a positive as well as negative effect on bank stability. On the one hand, as mandated by regulation, holdings should support subsidiaries facing adverse shocks via internal capital markets (Gilbert, 1991), thereby reducing insolvency risk at troubled affiliates. Moreover, even without capital transfers, the market perception of an implicit support guarantee by the holding may be enough to lower the subsidiary's share price volatility. However, incentives created by affiliation with a holding company could also motivate subsidiaries to take on more risk (Hughes et al., 1996), or facilitate 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 the

[1] For example, Federal Reserve Regulation Y of 1984 states that "a bank holding company shall serve as a source of financial and managerial strength to its subsidiary banks," while a 1987 Fed policy statement further details that a bank holding company "should stand ready to use available resources to provide adequate capital funds to its subsidiary banks during periods of financial stress." The same view is upheld in the Dodd-Frank Act of 2010, Title VI, Sec. 616, 38(A), which defines the precise meaning of 'source of strength' and clarifies expectations of BHCs to serve as such as source as an ongoing obligation.

stability of multibank holding company (MBHC) banks and independent banks reacts to an exogenous negative shock to net equity.

We study the reaction of market-based risk measures to an exogenous balance sheet shock, and how MBHC affiliation affects this response. We focus on individual as well as systemic risk – the risk that the failure of a single institution may impose externalities on the entire banking system due to high interbank commonality. Because of the magnitude of the adverse effects of this risk on the real economy, studying the impact of holding affiliation on systemic risk is particularly relevant in the banking industry. How holding affiliation affects systemic risk is far from obvious. On the one hand, bank holding company dynamics may lead banks to reduce this risk if that bolsters their resilience to tail events. On the other hand, holding affiliation could also increase commonality if banks are exposed to similar shocks because of correlated investments dictated by a holding-wide policy. To the best of our knowledge, ours is the first paper to study this relationship.

Next, we explore why this might be the case and examine whether holding company characteristics play a role in shaping stability at MBHC banks, and whether risks spill over to unaffected holding members. We complement our understanding of bank stability 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 not covered by assets. With the insurance sector covering significantly fewer hurricane claims than expected,[2] 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 MBHC-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

[2] For a discussion, see "Katrina damage ruling bad news for homeowners," *The Houston Chronicle*, August 15, 2006. 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).

correlated with their inherent resiliency.

Using a difference in difference approach we find that banks that are part of a MBHC 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 MBHC affiliates hit by the shock, but this effect is reversed as the liquidity of the holding increases. By contrast, holding charter value and size do not seem to matter for risk mitigation. While we cannot provide conclusive evidence on the dominant mechanism behind MBHC banks' higher resilience, our results are consistent with internal capital markets making MBHC banks safer.

We also examine whether unaffected banks in affected holdings experienced spillover effects from exposed banks in the holding, as previous literature has suggested. We do not find a significant effect on other unaffected banks at quarterly frequency.

Our additional event study shows significant differences in the abnormal returns associated with MBHC affiliation. Affected MBHC 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. Furthermore, when studying higher-frequency (daily) data, we do observe evidence of spillover effects on unaffected banks. 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 could explain our findings. In addition, we also run a placebo test moving 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 bank risk 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 are still a priori unknown. Secondly, we show that our results are robust by controlling for time-varying observable characteristics. 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. Finally, we show graphically that our results are not driven by differences in the disaster exposure of independent versus MBHC banks.

One remaining concern could be the endogenous nature of MBHC affiliation. However, this should not be an issue in our setting since the banks in our sample did not change their affiliation status during the sample period. Thus, any difference between the two types of banks is accounted for by bank fixed effects.

We contribute to the existing literature along several dimensions. Our first contribution is to the literature on the benefits and costs of bank holding company affiliation. This literature has studied the effects 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 three 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). Finally, market data allows us to examine an additional channel, not yet studied in this literature, through which holding affiliation could affect banks' performance and stability: 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 extend the literature by studying the effect of holding affiliation on individual as well as systemic risk. In particular, to the best of our knowledge, we are the first to show that holding affiliation increases banks' resilience to systemic risk.

Our work is also related to the literature studying the effects of natural disasters on bank behavior. This literature has mainly focused on the effects on credit supply after a shock. For example, Garmaise and Moskowitz (2009) 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, which should presumably make them safer. Nonetheless, we show that even controlling for risk-based capital ratios, independent banks are more risky after the shock. 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. We extend this literature by also exploring the *systemic* stability of banks following a natural disaster. However, we do not focus on the mechanisms by which the disaster affects bank bank balance sheets, since they are extensively studied in Lambert et al. (2018).[3] Instead, we focus on the heterogeneous effect of holding company affiliation on bank stability and market valuation.

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 show how holding company affiliation affects bank stability.

Overall, our empirical work shows a positive effect of MBHC affiliation on the affected banks' market perception, and no evidence of spillovers within the holding, other than a very short-term effect on the cumulative abnormal return of unaffected MBHC banks. Our analysis suggests an internal capital market channel behind these results, however, data limitations prevent us from quantifying the exact mechanism through which MBHC affiliation affects this perception.

The remainder of the paper is structured as follows. The next section provides back-

[3] Another challenge to that kind of study is also the fact that accounting rules changed for the affected banks. See the Federal Financial Examination Council's (2005) special guidance.

ground 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 formed the bulk of the 2005 Atlantic hurricane season and made landfall in the US Gulf Coast between August 29 and October 27, 2005. Collectively, the three hurricanes inflicted the largest recorded damage in US history: US $162.5 billion. The largest part 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. Damage across multiple states, together with the fact that Louisiana was hit twice, 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. The hurricanes reduced banks' net equity by destroying the collateral on outstanding mortgage loans, leaving banks exposed to loan defaults no longer collateralized by assets.[4] On the other hand, the insurance sector covered significantly fewer claims than expected due to the water-driven (rather than wind-driven) nature of the damage, allowing insurers to argue in court that the damage was out of scope and giving rise to several class-action lawsuits.[5] The uncompensated loss of real estate 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).[6]

[4]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).

[5]For example, the state of Mississippi initiated a class-action lawsuit against insurers StateFarm, Allstate, USAA, and Nationwide. See *Jim Hood, Attorney General for the State of Miss. v. Mississippi Farm Bureau Ins., et al.*, Chancery Court of Hinds County, MS, First Judicial District, Docket No G2005-1642.

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

Figure 1 initially shows a clear downward trend in nonperforming loans for affected and 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 visibly 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) findings. 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 consistent with the existing literature.

These negative effects on bank balance sheets were somewhat mitigated by liquidity inflows from insurance payments and by government aid to consumers. However, as a whole, the negative effect prevailed (Noth and Schüwer, 2017; U.S. Government Accountability Office, 2012). Furthermore, households' deposit withdrawals motivated by uncertainty or liquidity needs may have exacerbated the negative liquidity shock for some banks (Federal Deposit Insurance Corporation, 2005)

The hurricane season also affected banks' investment opportunities. On the one hand, it negatively affected growth because of business disruptions in damaged areas; on the other, rebuilding activities boosted economic growth in these areas (Cortés, 2014). Previous research shows that the former effect dominated, at least in the short term (Strobl, 2011; Deryugina et al., 2013). Overall, the hurricane season negatively affected banks by increasing losses and reducing investment opportunities.

3 Data

We combine data from multiple sources to study the effect of the 2005 hurricanes on bank stability and returns. To calculate market-based risk metrics (MES, SRISK, market Z-Scores, market betas, and CAR) at the subsidiary level, we focus on individually-listed US commercial banks. We retrieve the stock prices of 329 banks, 294 of which we were able to match to balance sheet information from their Call Reports and, where applicable, to the FR-Y9C reports of their ultimate parent, before imposing sample restrictions.[7]

[7]We do not include 252 bank holding companies whose subsidiaries are not listed separately, since parent and subsidiary risk are commingled in the holding's stock price.

We define a bank as an independent if it is either a standalone bank or a one-bank holding company bank, based on the ultimate parent according to Bloomberg.[8] We group standalone and one-bank holding company banks together for two reasons. First, the literature has found that they behave similarly to each other and differently than MBHC banks (Ashcraft, 2008); and second, because we are interested in studying spillover effects to other affiliates in the holding.[9]

We identify the zones affected by the 2005 hurricane season by FEMA's official disaster declarations, issued at the county level. Affected banks are identified as those with positive mortgage lending exposure to counties with a disaster declaration.[10] The counties of each bank's mortgage lending are sourced from the HMDA data files, which contain the census tract of each mortgage loan for every mortgage lender in the US. We limit the sample period to six years (2002-2007) to avoid overlap with the financial crisis starting in 2008.

Finally, we exclude several new banks entering after the shock, as well as several banks whose treatment status is not fully certain (see the treatment definition below). The final sample thus consists of 237 banks; 159 are independent (121 unaffected, 38 affected) and 78 are MBHC-owned (55 unaffected, 23 affected). About two-thirds (38/61) of the affected banks are independent – a variation we use to explore their different resilience to exogenous shocks.

Our final sample includes independent banks and banks owned by regional and nationwide multibank holdings. Appendix A provides a list of the MBHC's in our sample by treatment status. Our data features both holdings with nationwide presence such as Bank of America and CapitalOne, and relatively more regional holdings, many of which had no presence in the Gulf Coast. Such regional holdings, especially those based on the West Coast and the Northeastern US, received no hurricane exposure, and their banks

[8]The Bloomberg data permits a direct identification of the ultimate parent at the time of retrieval, unlike the data available through the National Information Center (NIC), which can include relationships not governed by US banking statutes and ownership levels not meeting FR Y-10 reportability criteria. Having identified the ultimate parent, we still use the NIC tables top-down to double-check that there are no changes to sampled banks' ownership during the sample period.

[9]Our sample of independent banks also includes some one-bank holding company banks that are part of a diversified group containing non-bank firms. One concern could arise if such banks behaved differently from remaining independent banks, or similar to MBHC banks. In unreported tests, we examine whether this is the case and create a separate category for such independent banks. We find that both types of independent banks behave similarly once hit by the shock. We also confirm specifically that independent banks that are part of a diversified group behave differently from MBHC banks, consistent with the evidence in Ashcraft (2008). Because of this, and to avoid multicollinearity issues caused by the triple interactions, we consider only one category of independent banks across the paper, which includes both types.

[10]Destroyed mortgage collateral in hit counties is likely a more accurate proxy of a bank's hurricane exposure than its physical branch presence; Berrospide et al. (2016) show that 21% of the mortgage loans were extended to areas without physical branch presence.

were therefore assigned to the control group.

3.1 Treatment definition

To measure banks' exposures, we define a continuous treatment measure, *Exposure*, which identifies the affected banks. For each bank, *Exposure* equals the bank's fraction of mortgage lending to the disaster counties in the period before the shock (2002 to 2004). The loan amounts and locations are obtained from the HDMA data. Banks that did not lend to disaster counties before the shock have an *Exposure* equal to zero and form the control group.

FEMA can designate a county for two types of disaster assistance: individual assistance and public assistance. Individual assistance is intended directly for affected homeowners and correlates strongly with bank risk exposure; by contrast, public assistance alone correlates only weakly with mortgaged home damage.[11] We identify a county as hit if it was designated by FEMA for individual disaster assistance as of September 28, 2005 (for hurricanes Katrina and Rita) and November 8 (for hurricane Wilma).

To make sure that the control group is not contaminated by banks with uncertain exposure to the disaster, we clean up the control group by excluding several banks lending to counties with public assistance only. 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.[12]

FEMA's designation of disaster counties from the 2005 hurricane season is shown in Figure 2, with individual assistance counties shown in color. Among sampled banks, red counties are served by MBHC banks; orange counties are served by a mix of independent and MBHC banks, and yellow counties are served by independent banks only. In the figure, a bank is defined as treated if it had positive mortgage lending to a treated (colored) county during 2002-2004.

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. MBHC banks. Table 2 provides summary statistics of the *Exposure* variable.

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

[12] 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.

4 Holding company affiliation and stability

To analyze the role of holding companies in shaping the effect of a negative shock on bank stability, we first study how holding affiliation affects banks' market-based measures of systemic and individual risk. Market-based measures are higher-frequency, more granular, and predict bank performance better than supervisory CAMEL ratings (Berger, Davies, and Flannery, 1998; Cole and Gunther, 1998) used by previous studies (e.g., Ashcraft, 2008), which may be biased in favor of local conditions (Agarwal et al., 2014). More importantly, market data incorporates the perception of stockholders about bank dynamics after the shock, which allows us to draw additional inferences about mechanisms other than internal capital markets affecting the stability of MBHC banks (such as implicit guarantees or contagion).

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 proxies a bank's individual distance to default, MES captures the comovement between the bank and the rest of the financial system. Therefore, we use MES to capture the system-wide effect of the hurricane shock. For robustness, we also consider SRISK and market betas.

4.1 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. This measure has been shown to be a powerful tool to identify systemically important banks (Acharya et al., 2017).[13] 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

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

[13] Acharya et al. (2017) show that MES, measured before the crisis, was a good predictor of stressed US banks during the crisis.

where $Index_{i,d}$ is a value-weighted index of all sampled banks excluding bank i to avoid a mechanical relation between the bank's return and the index return. We take the negative value of this measure for ease of interpretation. Thus, higher values of this measure indicate a higher contribution to systemic risk.

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:

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

Z-Score is widely used in the literature examining banks' stability (e.g., Demirguc-Kunt and Huizinga, (2010); Houston et al., (2010) and many others). This measure captures banks' buffers, measured by its returns, and their risks, measured by the returns' standard deviation. Z-Score is then a measure of distance to insolvency; a higher value of this variable indicates better bank soundness.

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 MBHC banks. In the full sample (Panel A), the average Z-Score for the control group is 55.98, with a standard deviation of 33.95. 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, MBHC 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 MBHC affiliation and stability. To this end, we estimate variations of the following panel data model:

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

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.[14] We exclude the crisis period to avoid biases arising from changes in bank behavior. However, our main results regarding the role of MBHC affiliation are robust to longer and shorter time periods.

The variable $Exposure_i$ is the continuous treatment bank-level variable defined in section 3.1. 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 MBHC has on bank stability. Therefore, we further interact the fourth term in (3) with a dummy variable indicating whether the bank is independent, $Independent_i$. Our coefficient of interest is then β_3, which captures the differential effect on affected independent banks over affected MBHC banks.

We also include bank fixed effects d_i in all models to control for time-invariant unobserved characteristics.[15] 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.[16] 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. A full description of the variables and their sources is given in Appendix B.

[14]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' stability. As a robustness test, however, we do include quarter-year fixed effects.

[15]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 $Independent_i * Exposure_i$.

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

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 Section 4.3.

4.2 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 multibank 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 find a negative, but insignificant effect of the 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. The model for systemic risk displays similar results. Column (2) likewise does not show any significant effect of the 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 stability. In particular, one would expect an increase in insolvency risk, driven by the large credit losses experienced by banks after the disaster. Furthermore, business conditions worsened and depositors' uncertainty and liquidity needs may have led to increased deposit withdrawals. Although some banks received large inflows of insurance payments and consumer aid during this period, the literature finds that overall, the negative effect dominated (Noth and Schüwer, 2017).[17] Thus, we should observe a negative effect on individual banks' risk. 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 remaining 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 stability could be positive as well as negative. For example, the Federal Reserve has a supervisory expectation that a bank holding company should serve

[17]This seems plausible since at least 40% of the flooded properties in Louisiana were not covered by federal flood insurance (Federal Deposit Insurance Corporation, 2005).

as source of financial strength for its subsidiaries. Throughout the years, this expectation has been conveyed through the Federal Reserve's Regulation Y, its 1987 policy statement on the subject, and, most recently, by the Dodd-Frank Act of 2010.[18] A MBHC thus 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 MBHC banks is likely to be different.[19] 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 for affected independent banks, 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 MBHC 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.

Regarding systemic risk, we find a stronger positive effect for affected independent banks than for MBHC 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 MBHC banks is only weakly significant, as shown by the interaction term between the *Post* and *Exposure* variables. The coefficient equals -0.03,

[18]The Dodd-Frank Act defines the term 'source of strength' as "the ability of a company that directly or indirectly owns or controls an insured depository institution to provide financial assistance to such insured depository institution in the event of the financial distress of the insured depository institution." (Title VI, Sec. 616, 38A).

[19]Furthermore, since these effects are not necessarily mutually exclusive, more than one effect may shape bank stability.

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 multibank holding.

The above results show that banks that are part of a MBHC are more resilient to shocks than independent banks. We find this result both for individual as well as systemic risk. This evidence is consistent, for instance, with internal capital markets enhancing their stability, or with implicit guarantees affecting the market's perception. Furthermore, the evidence with respect to systemic risk is consistent with holding company dynamics that reduce interbank commonality and bolster their resilience to tail events. However, other mechanisms could also explain our results. We explore some alternative mechanisms in Section 4.4 and study whether holding company characteristics exacerbate or mitigate the resiliency of holding affiliates, and the effects on other banks in the same holding. Prior to 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.

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

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 we capture 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, are uncertain.

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 MBHC banks. Figure 3 shows the evolution of the average residuals for independent and MBHC 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 MBHC-affiliated 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 MBHC 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 Panel A 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 Panel A in Table 4. The evidence from these models shows that our results remain unchanged when controlling for the above covariates. Therefore, the above results 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 Panel A in Table 4; our results continue to hold. Thus, imbalances between control and treated banks do not explain our results. In addition, the effect on individual risk for affected MBHC banks turns positive in the model in column (5), suggesting that individual risk decreases for these banks. This positive effect might be driven by capital injections from the parent, or the market perception on this parental support. We will come back to this point in the next sections.

One remaining concern is that independent banks might be more exposed to affected coastal regions than MBHC banks. We confirm this is not the case in Figure 2, which shows the spatial distribution of independent and MBHC bank lending in the affected area. The figure shows that, if anything, it was not independent, but MBHC banks that were more exposed to the shock through their mortgage lending, as shown by the large orange area (served by both types of banks) and red area (only MBHC banks) in the figure. Pre-shock lending to the presumably harder-hit coastline was also dominated by MBHC banks.

Other robustness tests and discussion. Independent banks might be located in, for instance, riskier demand counties than MBHC banks. We include banks' location county-year fixed effects to control for differences between the two bank types that are driven by factors related to bank location. These fixed effects allow us to compare the two bank types in the same location-year. Results are shown in the last two columns of Panel A in Table 4. Our results remain unchanged when controlling for this.

We also test whether a different definition of risk affects the robustness of our results. We consider two alternative measures: banks' SRISK and their market betas. The first measure captures 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 (Brownlees and Engle, 2017).[20] Thus, higher values of *SRISK* indicate a higher contribution to systemic risk. The second measure captures a bank's systematic risk. This measure is the estimated *beta* of a capital asset pricing model using daily stock market

[20]Specifically, the SRISK is computed as follows: $SRISK_{it} = W_{it}\left[kLVG_{it} + (1-k)LRMES_{it} - 1\right]$, 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).

returns for each bank and the S&P 500 daily returns.

The results using these alternative measures are presented in Panel B of Table 4. The results hold when using these measures of systemic risk. Column (1) in this Panel shows a decrease in systemic risk for MBHC banks and a marginal increase in this risk for independent banks. As mentioned earlier, the decrease in systemic risk for MBHC might be driven by the local nature of the shock, which decreases co-movement with the rest of the banks in the system. The second column in this table indicates that systematic risk also increases for independent banks, as suggested by the triple interaction term in this model.

We found that MBHC banks are more resilient to a negative shock than independent banks. However, MBHC banks may be more geographically diversified than independent banks, which could also explain the higher resiliency of holding affiliates. We test whether this is the case by computing a geographic concentration index, HHI, defined at the highest level of ownership (holding-level for MBHC banks, and bank-level for independent banks) as the Herfindahl index of mortgage loans across counties (the sum of squared county-level lending shares over total mortgage lending in 2004).[21] A higher HHI implies higher geographic concentration and, thus, lower geographic diversification in lending. We show the results of this test in Panel A of Table 5. In the first two columns, we replace the MBHC affiliation dummy by the bank geographic concentration measure, HHI. When not controlling for the heterogeneous effect of MBHC affiliation, the simple interaction term capturing the effect of the shock on risk for affected banks suggests that individual risk increased after the shock, as indicated by the model in column (1). The triple interaction term is significant at 1% only for the systemic risk model, suggesting that affected banks with more concentrated lending in the pre-shock period experienced a larger increase in systemic risk after the shock.[22]

In the last two columns, we include the interactions with the *Independent* dummy. Columns (3) and (4) show that the triple interaction with holding affiliation is highly significant in both models, and with the expected signs. The triple interaction with the geographic diversification measure HHI remains significant only for the systemic risk model. This confirms that the factor driving the differential effect for MBHC banks is

[21]HHI measures are standard in the geographic diversification literature. For recent examples, see Goetz et al. (2016), among others.

[22]The increase in systemic risk for banks with concentrated lending is consistent with a significant shock for these banks that increases correlatedness with other affected banks in the US. The (weakly) positive effect on individual risk can be explained by stronger monitoring (Sussman and Zeira, 1995) and organizational economies (Berger et al., 2005) arising from more concentrated lending, which may lead these banks to be in a better position to withstand the shock.

their affiliation with a holding and not higher geographic diversification.

We also consider the distance across counties banks are exposed to. To this end, we use a crude proxy of distance diversification used in the literature: the number of states where the holding (or independent bank) lends (e.g., Fraser et al., 1997). We now add to our baseline models a triple interaction term of the $Post$ and $Exposure$ variables with a $High\ states$ dummy variable, which indicates whether the number of states the holding (independent bank) is lending to is above the median number of lending states. Results are displayed in Panel B of Table 5. The results are similar to the ones in Panel A. Affected independent banks experienced a larger increase in individual and systemic risk after the shock, as shown by sign and significance of the relevant triple interaction term. The triple interaction term with the high states dummy is negative and significant at 1% in all models. This is consistent with the results in Panel A: affected BHC (or independent) banks with more geographically diversified lending in the pre-shock period experienced a decrease in systemic risk and a larger increase in individual risk after the shock.

Lambert et al. (2018) show that affected independent banks increased their risk-based capital ratios after the shock, while MBHC banks did not. Higher capital ought to make independent banks safer, contrary to what we find. This suggests higher risk-based capital ratios alone do not explain our results; nevertheless, we further demonstrate this 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 (total risk-based capital over total risk-weighted assets). In column (1), only the interaction between $Post$ and $Capital\ ratio$ is statistically significant at 5%. The positive coefficient in this interaction term suggests that after the shock, higher-capitalized banks experienced lower insolvency risk, as expected. 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 $Post * CapitalRatio * Exposure$, 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 significantly different risk 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 latter 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

MBHC banks do not drive our results.

Another concern is that independent and affiliated banks may differ across 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 Panel A of Table 4. We further account for these differences and use propensity score matching to match independent banks to similar affiliated banks. 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 C. Our results hold when using this matched sample. Hence, differences between independent and MBHC banks do not seem to explain our results.

Finally, we also run four unreported tests. First, we shorten the *Post* period by one year so it spans from 2005:Q3 to 2006:Q4. Second, we include quarter-year fixed effects to account for unobserved time effects that might be related to bank soundness. Our results remain mostly unchanged in these tests. Third, since we argue that the main channel through which banks are affected by the shock are losses incurred 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 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. Fourth, we estimate our risk model focusing on MBHC 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 rest as a result of large insurance payments. This effect would go against our results finding MBHC banks being safer. Still, we explicitly test for this by creating a dummy variable equal to one if the bank has at least one insurance company in the holding.[23] We do not find any differential effect for such holdings. Our previous results remain unchanged.

4.4 Understanding multibank-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

[23] We exclude life insurance companies from this dummy as they do not cover property-casualty claims.

banks. In this section, we aim to further understand MBHC mechanics and examine whether bank resiliency is a function of holding characteristics, and whether there are spillover effects within holdings. This study also sheds light on the potential mechanism through which holding affiliation affects banks' risk.

4.4.1 Multibank-holding-company banks and holding characteristics

We examine whether resiliency depends on holding characteristics. For this, we estimate our model on the MBHC banks only, and include a triple interaction between the *Post* and the *Exposure* variables with a number of holding characteristics.

The 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).[24] 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. Hence, we first examine whether the holding's liquidity plays a role in shaping stability at MBHC banks. Observing that holding liquidity mitigates the effect of the shock would be most consistent with a liquidity shock that is mitigated by internal capital markets.

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 MBHC 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.[25] 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. This result likely reflects the opportunity cost of holding a larger amount of very liquid assets.

Results for the MES are in line with those 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

[24]This has also been shown by Shin and Park (1999) for non-financial firms.
[25]This calculation is based on the mean bank according to the *Exposure* measure.

suggest that systemic risk increases when MBHC 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.

Liquidity buffers are likely correlated to other holding characteristics that may affect bank stability. We account for this by including holding company level controls in the models in column (3) and (4) for the Z-Score and MES, respectively. The added holding company controls are leverage, size measured as the logarithm of the assets, and ROA. Appendix D reports summary statistics of the holding's controls. The results in these models are similar: 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.

Higher holding charter value may mitigate the negative effect of the shock if good investment opportunities or deposits tend to move to well-known holdings' affiliates after the shock. High charter value banks could also reduce risk-taking after the shock in order to avoid failure. Thus, in a second test, we use holding book-to-market ratios as proxies for banks' charter value (Keeley, 1990). Observing that a lower book-to-market ratio decreases the negative effect of the shock would be consistent with such a charter value effect. The next four columns in this table present the results of this test. Similar to Table 3, we do not observe a significant effect for affected MBHC banks after the shock when we do not control for the non-monotonic effect of liquidity holdings. More importantly, this result does not vary with holding charter value, as suggested by the insignificant coefficient of the triple interaction term in this model. This evidence suggests that holdings' charter value does not play a role in shaping the resiliency of MBHC banks.

Finally, we examine whether the effect on bank risk is a function of holding size. Large holdings are more likely to receive government support than small ones. Depositors might also be less likely to withdraw deposits from affiliates of large or well-known holdings because of this perception. Thus, observing a size-driven positive heterogeneous effect would be consistent with a liquidity shock being mitigated by the higher likelihood of government support or smaller deposit withdrawals. The last four columns show, as in the previous models, the absence of a significant effect for affected MBHC banks after the shock when we do not include the heterogeneous effect of holdings' liquidity. In addition, the coefficient of the triple interaction term with size is not significant in these models.

This result suggests that the effect on bank risk does not depend on holding size through, for instance, reducing the likelihood of deposit withdrawals or increasing the likelihood of government support.

There may be other mechanisms that could explain MBHC banks' higher resilience.[26] While we cannot provide conclusive evidence on the dominant mechanism behind MBHC banks' higher resilience, the evidence in this section is most consistent with the hurricane season negatively affecting liquidity at banks and that being mitigated by the functioning of internal capital markets in multibank holdings.[27]

4.4.2 Spillover effects to other banks in the group

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).[28] 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 stability of unaffected MBHC 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.

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 on MBHC banks only:

[26]For instance, if independent banks, which tend to be more local, feel more pressured to be charitable and give up shareholder value by extending negative-NPV loans, while MBHC banks do not have this pressure, and invest in positive-NPV loans.

[27]It is important to note that internal capital transfers can benefit other shareholders so that banks' received transfers could be smaller. However, even though the value increase might be smaller than the transfer itself, we find a significant heterogeneous effect of the holding's liquidity on risk. The potential bias works against finding this effect. Thus, if the actual transfer is larger than the subsidiary's value increase, in reality we should observe an even larger effect than the one we find.

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

$$Risk_{it} = \alpha_0 + \sum_i \alpha_{1,i} d_i + \alpha_2 Post_t + \beta_1 Exposure_i * Post_t + \beta_2 Group\ Exposed_i * Post_t$$
$$+ \beta_3 Exposure_i * Post_t * Group\ Exposed_i + \epsilon_{it}. \tag{4}$$

If an unaffected bank in an affected holding suffers spillovers 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 MBHC 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 MBHC banks; and that there is no evidence of increased risk for unaffected banks in the holding.

5 Holding company affiliation and stock returns

We have shown that MBHC 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; and more importantly, we examine whether the market distinguishes between independent and MBHC banks in its reaction. To this end, we perform an event study and measure changes in shareholder value resulting from the shock, while examining whether this valuation relates to holding affiliation.

5.1 Cumulative abnormal returns

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

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{Mt}\right), \tag{5}$$

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 MBHC 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 MBHC 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:

$$CAR_i = \alpha + \beta_1 Exposure_i + \beta_2 Independent_i + \beta_3 Exposure_i * Independent_i + \sum_k \gamma_k X_{k,i} + \epsilon_i, \tag{6}$$

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.

We should observe a negative effect on CARs of affected independent and MBHC banks as a result of the negative shock on banks' balance sheets. Furthermore, if MBHC affiliates' dynamics after the shock are perceived as value-reducing by the market we should observe a stronger negative effect for these banks. These dynamics can reduce affiliates' perceived value if, for instance, capital injections from the parent are perceived as inefficient cross-subsidies, thus over-investing in negative NPV projects at the subsidiary level (Scharfstein and Stein, 2000).[29] If instead, the markets perceive the MBHC banks' dynamics as value-enhancing, which offsets the negative effect of the shock, we should observe a positive net effect on affected MBHC banks. Such value-enhancing dynamics may arise if, for instance, capital injections are deemed as positive by the market, or investment opportunities or deposits increase for these banks after the shock. As mentioned earlier, we have found evidence consistent with internal capital markets being the dominant driver of these dynamics. However, since we do not observe internal capital transfers directly, other mechanisms cannot be ruled out.

5.2 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 those found in the previous section. There is a positive and statistically significant effect on affected MBHC banks over all time windows. The positive effect on affected MBHC banks suggests that the potential MBHC dynamics are perceived by the market as positive and this effect offsets the negative direct effect of the hurricane. There is a negative and statistically significant net effect on affected independent banks' CARs after the shock, consistent with our previous findings. The effects also suggest economic significance. Based on the estimates in column (4), one standard deviation increase in a MBHC 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.

We perform a placebo test on this event study and calculate the CAR 10 days ahead of the actual dates the hurricanes hit. To ensure a clean placebo test, we study the effects on CARs only one and two days after the placebo shock.[30] The results of this test are

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

[30] Longer post shock time windows would overlap with the actual event. Thus, the test would not be clean as it would capture the effect of actual post-hurricane days. Furthermore, since we consider the effect of three consecutive hurricanes, later hurricanes' placebo abnormal returns may capture abnormal returns related to earlier hurricanes. This would lead us to find a false significant effect, even though we

shown in Table 11. As shown in this table, we do not observe any significant effect on CARs when shifting the shocks several days ahead, as expected. This evidence indicates that banks' returns reacted after the shock hit and not before.

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 internal capital markets drive holding dynamics after the shock, the market would expect the potential reallocation of resources towards hit banks to reduce guarantees and resources available to unaffected banks; hence 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 MBHC 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 12. Results in this table show that affected banks increase their CARs after the shock, both when they are the only affected bank and 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 in Table 10 for MBHC 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. It suggests that the market expects a negative effect on such unaffected banks; this could be because of the expectation of moving resources away or reduced support from the parent. This effect is economically significant, too. 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 compared to the mean of this variable (-0.25).

Overall, the evidence in this section is consistent with affected MBHC banks performing better than independent banks after the shock. The positive stock market valuation of MBHC banks after the shock suggests that potential MBHC dynamics are perceived as value-enhancing by the market. In addition, the negative effect on stock returns of

are shifting the shock dates. Hence, we focus on the first two days after the shock, when the effect should be more closely related to each hurricane.

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.

6 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 MBHC affiliation on bank performance.

We show that MBHC 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 and betas. 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 MBHC banks versus independent banks; stock market value increases for affected MBHC banks, but decreases for independent banks after the shock. This suggests that potential MBHC 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.

Our findings are important in view of the ongoing discussion of bank holding company regulation after the 2008 crisis, including the additional restrictions on holding companies in terms of capitalization, management, lending limits, and mergers and acquisitions introduced by the Dodd-Frank Act and the recent relaxation of these restrictions by the Economic Growth, Regulatory Relief and Consumer Protection Act of May 2018.

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. However, this paper suggests that bank holding companies may play an underappreciated role in stabilizing the systemic risk of their affiliates, and shows evidence that the market values parental support in the immediate aftermath of a shock. If holdings allocate internal liquidity efficiently, then disbursing government liquidity through multibank holdings and letting it trickle down to those subsidiaries that need it may be optimal.

To the best of our knowledge, this is the first paper to study how MBHC affiliation affects banks' market-based risk measures. In addition, our paper's empirical strategy allows us to compare how independent and MBHC banks react to the same exogenous shock, and how their risks are affected.

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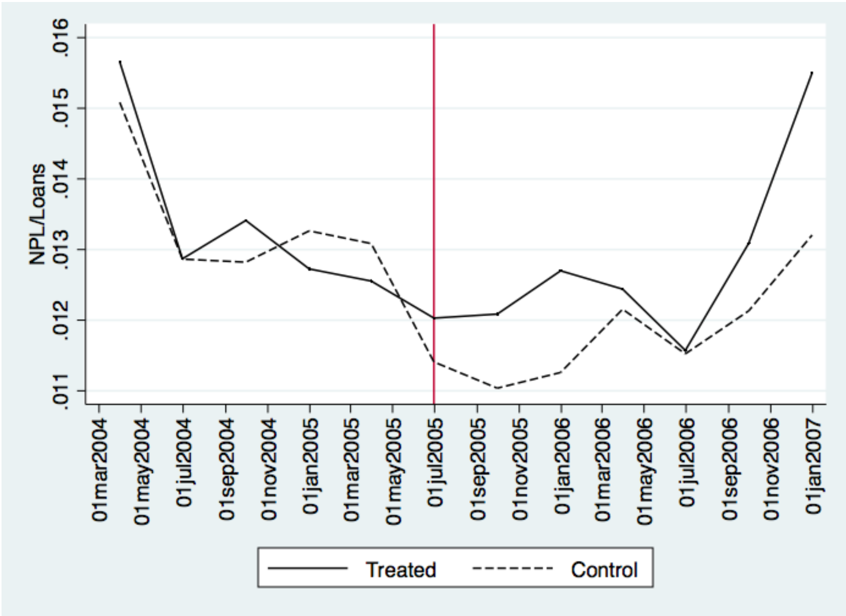
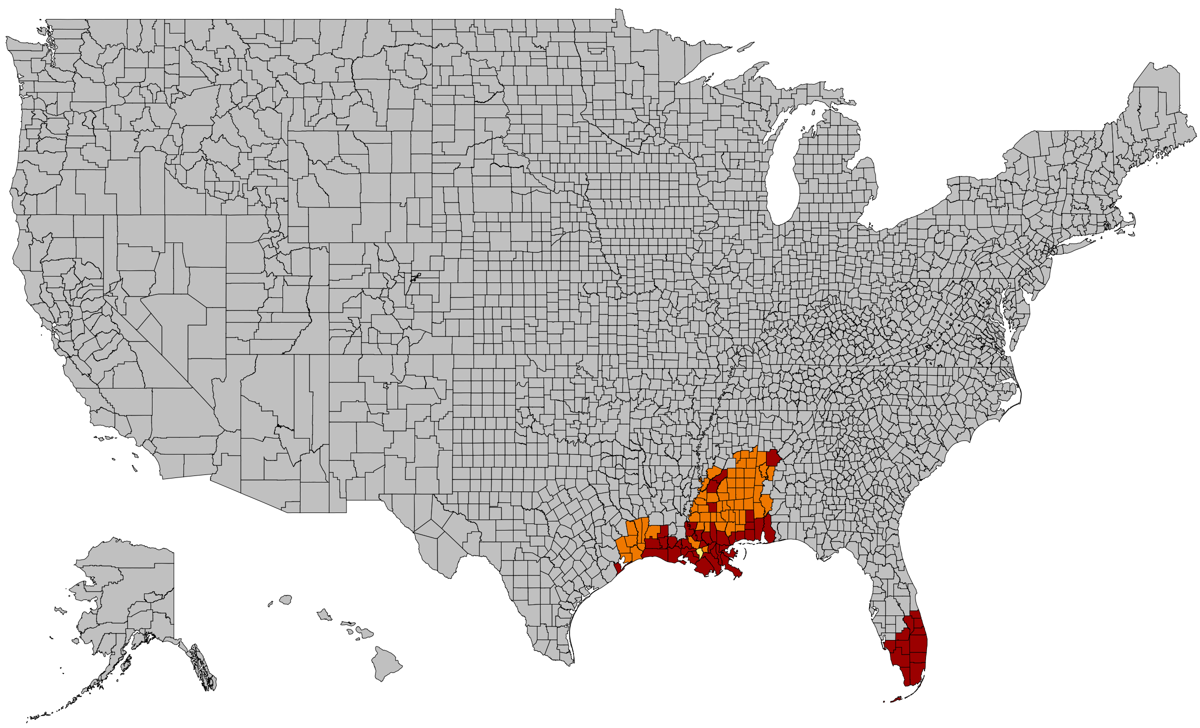
Figures

Figure 1. Evolution of Nonperforming Loans



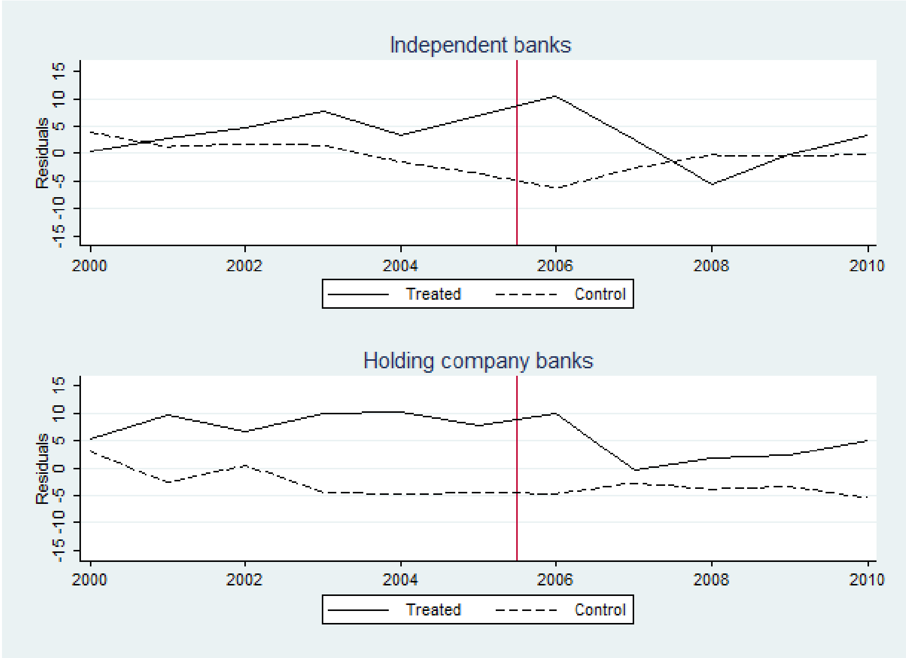
Evolution of nonperforming loans as a share of total loans for treated and control banks over time. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04.

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



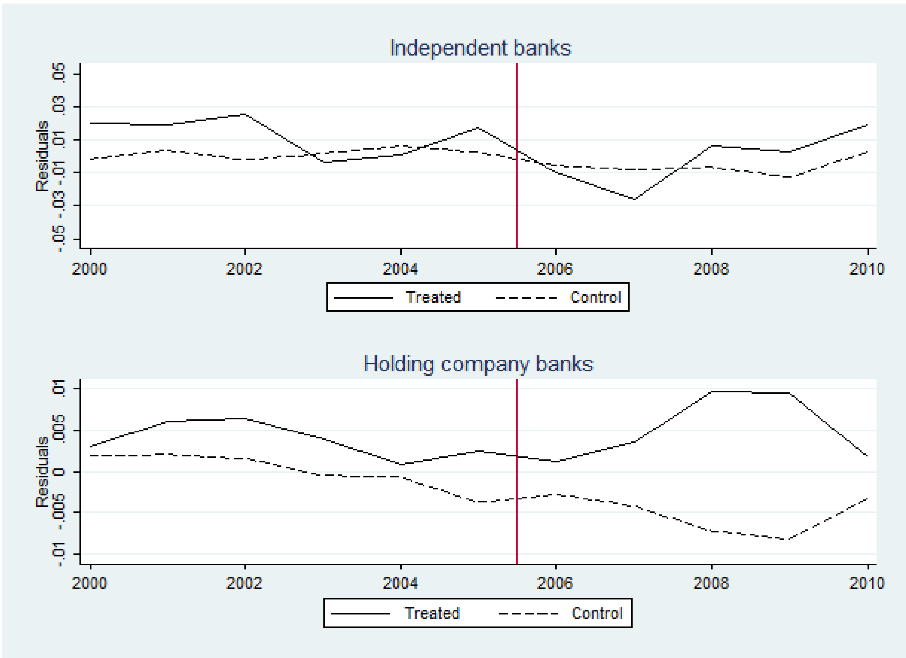
The colored area shows counties affected by hurricanes Katrina, Rita and Wilma. Affected counties are color-coded as follows: yellow - served by independent banks; orange - served by independent and MBHC banks; red - served by MBHC banks. A bank is defined as treated if it had positive mortgage lending to at least one of the colored counties 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, and defined as independent if it is either standalone or a one-bank BHC.

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 it is either standalone or a one-bank BHC.

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 MBHC banks. A bank is defined as treated if it had positive mortgage lending to an affected county during 2002-04, and defined as independent if it is either standalone or a one-bank BHC.

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: MBHC 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 MBHC 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 it is either standalone or a one-bank BHC. 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 B.

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

Panel A	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

Table 4: Robustness (cont.)

Panel B	SRISK	Beta
	(1)	(2)
Post	-0.0004	0.309***
	(0.0004)	(0.108)
Post*Exposure	-0.030**	-1.128
	(0.012)	(0.738)
Post *Independent	-0.0002	-0.131
	(0.0007)	(0.130)
Post *Independent*Exposure	0.031**	1.624**
	(0.012)	(0.757)
Bank FE	Yes	Yes
Observations	2,201	1,587
R-squared	0.07	0.05

This table presents the results of regressions studying the effects of the hurricane season on bank risks. The dependent variables in panel A are banks' Z-Score and MES. The dependent variables in panel B are banks' SRISK and market Beta. *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 B. 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)
Panel A: HHI				
Post	7.814***	0.00118	7.109**	0.00277
	(2.973)	(0.00196)	(2.914)	(0.00193)
Post*Exposure	-30.48**	-0.0185*	12.20	-0.0668**
	(14.70)	(0.0103)	(19.59)	(0.0262)
Post*HHI	7.034	0.00162	6.913	0.00277
	(6.148)	(0.00576)	(6.737)	(0.00648)
Post*Exposure*HHI	68.88*	0.159***	66.53	0.156***
	(40.82)	(0.0599)	(46.78)	(0.0454)
Post*Independent			0.942	-0.00301
			(3.419)	(0.00294)
Post*Independent*Exposure			-45.93**	0.0540**
			(21.50)	(0.0253)
Bank FE	Yes	Yes	Yes	Yes
Observations	2,973	2,269	2,973	2,269
R-squared	0.032	0.007	0.032	0.009
Panel B: Number of lending states				
Post	9.905***	0.002**	10.008***	0.002**
	(1.546)	(0.001)	(1.546)	(0.001)
Post*Exposure	-3.421	0.036***	8.794	0.018***
	(3.949)	(0.004)	(6.252)	(0.006)
Post*High states	2.87	-0.00008	3.674	-0.0007
	(3.252)	(0.002)	(3.798)	(0.002)
Post*Exposure* High states	-38.694***	-0.057***	-39.401***	-0.057***
	(8.033)	(0.008)	(7.467)	(0.005)
Post*Independent			2.095	-0.001
			(3.555)	(0.002)
Post*Exposure*Independent			-45.220***	0.056***
			(15.629)	(0.016)
Bank FE	Yes	Yes	Yes	Yes
Observations	3,082	2,338	3,082	2,338
R-squared	0.03	0.01	0.03	0.01

This table presents the results of regressions studying the effects of the hurricane season on bank risks using two geographic diversification measures (HHI and the number of lending states). The dependent variables are banks' Z-Score and MES. *Post* equals one from the third quarter of 2005 onwards. *Exposure* is a continuous variable denoting the share of mortgage loans extended to FEMA-designated disaster areas by each institution during the pre-shock period. *Independent* equals one if the bank is independent. *HHI* is the sum of the squared shares of an institution's mortgage lending to each county over its total mortgage lending using data for 2004. *High states* is a dummy equal to 1 for institutions lending to more than the median number of states in the sample (3 states). *HHI*, *High States* are constructed on the highest level of ownership (holding-level for holdings, bank-level for independent banks). 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 regressions studying the effects of the hurricane season on the banks' risks. The dependent variables are MES and $Z-Score$. *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. *Capital ratio* corresponds to the total risk-based capital over total risk-weighted 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 7: MBHC Banks and the Role of the Holding

	Z-Score (1)	MES (2)	Z-Score (3)	MES (4)	Z-Score (5)	MES (6)	Z-Score (7)	MES (8)	Z-Score (9)	MES (10)	Z-Score (11)	MES (12)
Post	4.870	0.00489	0.773	0.00496	7.187**	0.00573**	3.024	0.00446	15.28	0.0371*	11.40	0.0352*
	(6.297)	(0.00549)	(6.927)	(0.00493)	(3.115)	(0.00264)	(3.846)	(0.00295)	(26.66)	(0.0205)	(26.54)	(0.0187)
Post*Exposure	-404.5**	0.380**	-464.2*	0.404**	77.63	-0.0620	77.03	-0.0619	71.07	-0.0608	22.51	-0.0438
	(198.6)	(0.161)	(231.1)	(0.178)	(50.17)	(0.0555)	(54.20)	(0.0530)	(229.4)	(0.168)	(242.6)	(0.156)
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)								
Exposure*Book to market$_{Holding}$					0.321	-0.00193***	-0.260	-0.00245**				
					(2.027)	(0.000474)	(2.480)	(0.00107)				
Post*Book to market$_{Holding}$					0.000145	-8.66e-05	-0.00701	-7.76e-05				
					(0.0708)	(6.81e-05)	(0.0720)	(6.24e-05)				
Post*Exposure*Book to market$_{Holding}$					-2.420	0.00197	-1.772	0.00190				
					(1.838)	(0.00182)	(1.889)	(0.00166)				
Exposure*Log(assets)$_{Holding}$									21.89	-0.0185	43.17	-0.0224
									(43.47)	(0.0617)	(59.21)	(0.0688)
Post*Log(assets)$_{Holding}$									-0.582	-0.00213*	-0.364	-0.00203*
									(1.578)	(0.00118)	(1.580)	(0.00108)
Post*Exposure*Log(assets)$_{Holding}$									-2.745	0.00269	-0.00553	0.00154
									(13.28)	(0.00992)	(13.88)	(0.00919)
Liquid/TA$_{Holding}$	-257.5**	-0.0598	-232.2*	-0.0640			-234.5**	-0.0877			-225.4**	-0.0563
	(108.6)	(0.126)	(118.7)	(0.133)			(102.8)	(0.116)			(111.0)	(0.109)
Book to market$_{Holding}$					0.216**	5.47e-05	0.223**	5.74e-05				
					(0.0954)	(3.85e-05)	(0.0970)	(3.80e-05)				
Log(assets)$_{Holding}$			10.83*	-0.000212			10.22*	0.000523	10.81	0.00257	8.550	0.00135
			(5.778)	(0.00601)			(5.926)	(0.00662)	(6.800)	(0.00546)	(6.570)	(0.00612)
Leverage$_{Holding}$			93.13	-0.0577			101.4	-0.0904			95.01	-0.0467
			(152.0)	(0.150)			(152.9)	(0.161)			(173.1)	(0.148)
ROA$_{Holding}$			-866.8***	0.452			-827.0***	0.409			-810.2***	0.417
			(189.6)	(0.293)			(185.5)	(0.305)			(188.6)	(0.302)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	797	691	797	691	779	688	779	688	797	691	797	691
R-squared	0.049	0.018	0.065	0.024	0.037	0.015	0.066	0.023	0.039	0.020	0.060	0.026

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. $Liquid/TA_{Holding}$ corresponds to the holding cash and balances from depository institutions as a share of assets. *Book to market*$_{Holding}$ is the holding's book value to market value ratio, $Log(assets)_{Holding}$ denotes the logarithm of holding assets, $Leverage_{Holding}$ is the holding's debt over assets, and $ROA_{Holding}$ is the holding's return on assets. All models are estimated for the sample of MBHC banks only. 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. All models are estimated for the sample of MBHC banks only. 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: MBHC 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 samples and four different time horizons (1, 2, 10 and 15 days post-shock). The table displays variables' means and standard deviations for the treated and control banks in the full sample in Panel A; for treated and control independent bank in Panel B; and for treated and control MBHC 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 it is either standalone or a one-bank BHC. The normalized difference in means is displayed in the last column.

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 the logarithm of assets, *Book to market* is the bank's book value to market value ratio, *Leverage* is the bank's debt over assets, 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 sample consists of all banks with non-missing values in the included variables. The cross-sectional regressions are estimated by OLS with robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 11: Cumulative Abnormal Returns – Placebo Test

	CAR one day	CAR two days
	(1)	(2)
Exposure	0.06	-0.57
	(0.56)	(0.71)
Independent	-0.02	0.08
	(0.07)	(0.11)
Independent*Exposure	0.04	0.34
	(0.58)	(0.77)
Log(assets)	0.012	-0.06
	(0.02)	(0.04)
Book to market	-0.001	0.002
	(0.001)	(0.002)
Leverage	0.70	1.73
	(1.58)	(1.51)
ROA	-6.90	-3.05
	(6.53)	(15.60)
Constant	-0.73	-0.72
	(1.38)	(1.38)
Observations	75	81
R-Squared	0.02	0.07

This table presents the results of a placebo test checking for anticipatory effects of hurricanes on banks' cumulative abnormal returns 10 days before each hurricane hit. The dependent variables are cumulative abnormal returns aggregated over 1 and 2 days after each placebo 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 the logarithm of assets, *Book to market* is the bank's book value to market value ratio, *Leverage* is the bank's debt over assets, 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 sample consists of all banks with non-missing values in the included variables. The cross-sectional regressions are estimated by OLS with robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 12: 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 the logarithm of assets, *Book to market* is the bank's book value to market value ratio, *Leverage* is the bank's debt over assets, 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 sample consists of MBHC banks only with non-missing values in the included variables. The cross-sectional regressions are estimated by OLS with robust standard errors (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Appendix A: Alphabetical List of Multibank Holding Companies by Treatment Status

With $\geq$ 1 treated banks	Without treated banks
Ameris Bancorp	BNC Bancorp
BB&T Corp	Bank of Hawaii Corp
Bank of America Corp	Bank of Marin Bancorp
Capital One Financial Corp	Bank of the Ozarks Inc
Comerica Inc	Bankwell Financial Group Inc
Farmers National Banc Corp	Banner Corp
Fifth Third Bancorp	Bay Commercial Bank/Walnut Cre
First Community Bancshares Inc	C&F Financial Corp
First Midwest Bancorp Inc/IL	CVB Financial Corp
Huntington Bancshares Inc/OH	Carolina Trust Bancshares Inc
Lakeland Bancorp Inc	CenterState Banks Inc
M&T Bank Corp	Central Valley Community Banco
Nicolet Bankshares Inc	Citizens & Northern Corp
Peoples Bancorp Inc/OH	Columbia Banking System Inc
Regions Financial Corp	ConnectOne Bancorp Inc
Sandy Spring Bancorp Inc	East West Bancorp Inc
SunTrust Banks Inc	FCB Financial Holdings Inc
Towne Bank/Portsmouth VA	FNB Bancorp/CA
United Community Banks Inc/GA	FNB Corp/PA
Valley National Bancorp	Farmers & Merchants Bancorp/Lo
WesBanco Inc	First Mid-Illinois Bancshares
Yadkin Financial Corp	Franklin Financial Network Inc
	German American Bancorp Inc
	Heartland Financial USA Inc
	Heritage Oaks Bancorp
	Hope Bancorp Inc
	Howard Bancorp Inc
	Mechanics Bank/Richmond CA
	Northfield Bancorp Inc
	Opus Bank
	PacWest Bancorp
	Pacific Continental Corp
	Pacific Premier Bancorp Inc
	Park Sterling Corp
	Southern BancShares NC Inc
	TriCo Bancshares
	Umpqua Holdings Corp
	United Bankshares Inc/WV
	WashingtonFirst Bankshares Inc
	Xenith Bankshares Inc

This table lists the multibank holding companies in our sample by the treatment status of their affiliate banks. Holdings with at least one treated bank are listed in the left column; those without treated banks are in the right column.

Appendix B: Variable Definitions

Variable	Definition	Source
Risk measures		
Z-Score	1+ the 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
SRISK	The expected capital shortfall of a bank conditional on prolonged marked decline.	Authors' calculation using stock price data from Bloomberg
Beta	Betas of a capital asset pricing model constructed using daily stock market returns for each bank on the S&P 500 daily returns	Authors' calculation using stock price data from Bloomberg
Cumulative abnormal returns		
CAR n days	Cumulated abnormal returns as defined in the model in section 5.1, eq. (5)	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 MBHC 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 standalone or a one-bank BHC	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
Book to market	Bank's book value to market value ratio	Authors' calculation using stock price data from Bloomberg and US Call Reports
Holding controls		
Log(assets)	Logarithm of assets	FR-Y9C reports
Leverage	Debt over assets	FR-Y9C reports
ROA	Net income over assets	FR-Y9C reports
Book to market	Book value to market value ratio	Authors' calculation using stock price data from Bloomberg and FR-Y9C reports
Liquid/TA	Cash and balances from depository institutions over assets	FR-Y9C reports

Appendix C: 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 D: Summary Statistics Holdings

	N	Mean	Std. Dev.	Min	Max
Log(assets)$_{Holding}$	1,075	15.150	1.832	12.254	18.955
Leverage$_{Holding}$	1,075	0.911	0.016	0.859	0.942
ROA$_{Holding}$	1,075	0.007	0.004	-0.0004	0.016
Book to market$_{Holding}$	1,010	12.707	47.738	0.036	513.271
Liquid/TA$_{Holding}$	1,075	0.032	0.016	0.013	0.117

Summary statistics for holding companies in our sample. The table shows statistics for 62 ultimate parents based on quarterly data for the years 2002–2007. Definitions and sources of control variables are listed in Appendix B.