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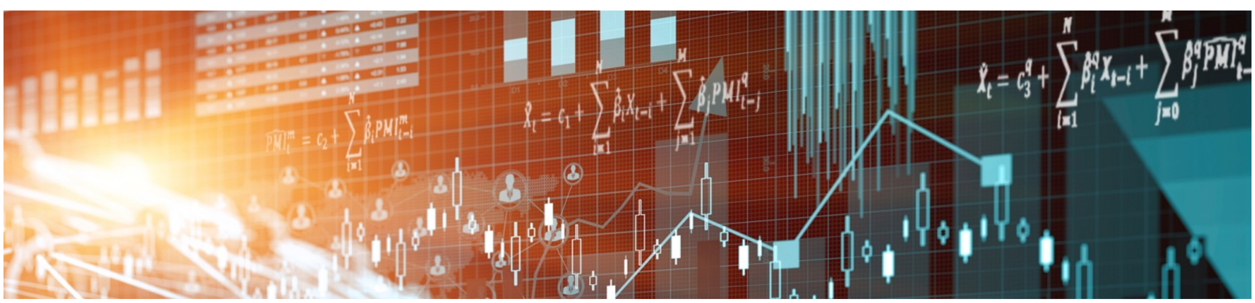
Staff Working Paper/Document de travail du personnel 2018-51

Multibank Holding Companies and Bank Stability



by Radoslav Raykov and Consuelo Silva-Buston

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Bank of Canada Staff Working Paper 2018-51

October 2018

Multibank Holding Companies and Bank Stability

by

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ISSN 1701-9397

Acknowledgements

Silva-Buston gratefully acknowledges the financial support of Fondecyt Iniciacion (project/folio 11150492). The views and opinions expressed are strictly those of the authors and do not represent the views of their respective institutions. The authors would like to thank Jason Allen, Adi Morel, Evren Damar and participants in the IFABS 2018 conference for useful feedback. Colin Charlton provided excellent research assistance.

Abstract

This paper studies the relationship between bank holding company affiliation and the individual and systemic risk of banks. Using the 2005 hurricane season in the US as an exogenous shock to bank balance sheets, we show that banks that are part of a holding parent company are more resilient than independent banks. Examining the impact of the liquidity of the holding on resiliency shows that banks are more fragile when the liquidity of the holding is lower, consistent with internal capital markets playing a role in stabilizing banks. We also show that banks whose holdings display low liquidity levels rebalance their portfolios towards riskier activities, such as non-traditional banking activities.

Bank topics: Financial stability; financial institutions
JEL codes: G1, G2

Résumé

L'étude porte sur la relation entre l'affiliation d'une banque à une société de portefeuille bancaire et le risque particulier et systémique des banques. En prenant la saison des ouragans de 2005 qu'ont connue les États-Unis comme exemple de choc exogène pour les bilans bancaires, nous montrons que les banques contrôlées par une société de portefeuille sont plus résilientes que les banques indépendantes. Pour ce qui est de l'effet de la liquidité d'une société de portefeuille sur la résilience de ses filiales, les banques apparaissent plus fragiles quand la société mère a peu de liquidités. Cette observation est conforme aux observations trouvées dans la littérature sur le rôle joué par le financement interne dans la stabilisation des banques d'un groupe. Nous montrons aussi que les banques aux societés moins liquides réorientent leur portefeuille vers des activités plus risquées, notamment vers les activités bancaires non traditionnelles.

Sujets : Stabilité bancaire; Institutions financières
Codes JEL : G1, G2

Non-technical Summary

The banking literature has discussed the benefits and costs of holding company affiliation on bank performance. On the one hand, holding-company banks can enjoy the support of their parent 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 banks can 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 and use an exogenous shock to bank balance sheets to study the net effect of holding company affiliation on bank stability. As an exogenous shock, we use the costliest natural disaster in US history: the 2005 hurricane season.

We show that holding-company banks are more stable than independent banks when affected by a negative shock. They display lower systemic risk levels, as measured by the MES and SRISK metrics, and lower individual risk levels, as measured by market Z-Scores. Furthermore, we show evidence that the cash of the holding plays a role in shaping their resiliency, consistent with an internal capital market story.

We also show how banks rebalance their portfolios after the shock. As the cash of the holding increases, holding-company banks transfer resources away from non-traditional banking activities and increase their real estate loans and bond holdings. The decrease in non-traditional banking activities is consistent with the increased stability of holding-company banks, as suggested by previous literature.

1 Introduction

The 2008 financial crisis has renewed interest in the main factors behind the individual and systemic risk of banks. One such factor may be holding company affiliation. The literature on multibank holding companies shows that banks that are part of a holding differ from independent banks in several dimensions, including their lending behavior (Houston et al., 1997), risk-based capital ratios (Lambert et al., 2018) and funding sources (Campello, 2002). Thus, the stability of these two kinds of banks is also likely to differ.

In principle, the effect of holding company affiliation on bank risk can be positive as well as negative. For example, holdings can support subsidiaries facing adverse shocks via internal capital markets (Gilbert, 1991), thereby reducing insolvency risk at troubled affiliates. Moreover, even if holdings do not channel funds to troubled subsidiaries, the market perception of an implicit support guarantee by the holding may be enough to lower the subsidiary's share price volatility. However, affiliation with a holding company could also lead to an increase in risks at subsidiary banks via higher risk taking (e.g., Hughes et al., 1996), or via contagion from other banks in the holding (e.g., Berrospide et al., 2016). The net effect of holding company affiliation on stability is thus not a priori clear. In this paper, we revisit this question from a new angle: we compare how holding-company-owned banks and independent banks react to an exogenous negative shock to net equity.

We study how the systemic and individual risk of banks respond to an exogenous negative shock to bank balance sheets and whether holding company affiliation affects this response. Furthermore, we explore why this may be the case and examine whether holding company characteristics (in particular, liquidity and capital levels), play a role in shaping stability at holding-company banks. Finally, we explore how this effect may take place and examine how banks rebalance their portfolios once hit by the shock.

As a shock, we exploit the costliest natural disaster in US history: the 2005 Atlantic hurricane season, which inflicted more than $162 billion worth of damage. Hurricanes reduce banks' net equity because they destroy the collateral on outstanding mortgage loans, leaving banks more exposed to defaults no longer covered by assets. This increases their losses given default, while default rates rise. With the insurance sector covering significantly fewer hurricane claims than expected after this disaster,[1] thousands of homeowners were left

[1] For a discussion of the causes, see Section 2 in Raykov (2015). 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).

without homes and insurance payouts, affecting their ability to service their mortgages and increasing bank losses.

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

Our data comes from multiple sources. We use daily stock return data from Bloomberg to compute quarterly systemic and individual risk measures (MES, SRISK and Z-Score) for publicly traded US commercial banks, and include balance sheet and income statement variables from the banks' Reports of Condition and Income (Call Reports). Since the main impact of the hurricanes on the banks' net equity occurs through the destruction of mortgage collateral, we use the spatial distribution of bank mortgage lending to affected counties during the pre-shock period to gage bank exposures to hurricane losses.[2] We define a continuous treatment measure, *Exposure*, as a proxy for a bank's losses, using the fraction of mortgage loans it extended to hurricane disaster zones designated by the US Federal Emergency Management Agency (FEMA) before the shock. Treated banks are defined as those with strictly positive *Exposure*. We obtain the locations of mortgaged properties and the amount of each loan from the Housing Mortgage Disclosure Act data files (HMDA). Banks that did not extend loans to disaster zones and thus have *Exposure* equal to zero are the control group.

To identify banks belonging to holding companies, we use information from Bloomberg on the ultimate parent of each institution. Banks that do not have a parent bank are considered independent. We also obtain balance sheet information about holding companies from their respective FR-Y9C reports. We follow the sampled banks between 2002 and 2007 to avoid overlap with the 2008 financial crisis. The final sample consists of 237 banks: 159 independent (121 non-treated, 38 treated) and 78 holding-company-owned banks (55 non-treated, 23 treated). About two-thirds of the treated banks are owned by holding companies

[2]This approach also allows for better identification compared with bank headquarters locations, because a bank headquartered just outside a disaster area may still have significant mortgage exposure to it.

– a variation that we use to explore differences between independent and holding-company banks.

We find that banks that are part of a holding company are more resilient to shocks than independent banks; this evidence holds in terms of both individual and systemic risk. Furthermore, our findings show that risk metrics also increase for holding company affiliates hit by the shock, but this effect is reversed as the liquidity of the holding increases. These results suggest that internal capital markets may play a role in reducing risk at holding-company banks. We also examine whether unaffected banks in affected holdings experienced spillover effects from exposed banks in the holding, as previous literature has suggested. We examine whether unaffected banks in such holdings display an increase in their individual and systemic risk, but do not find a significant effect. Thus, the evidence suggests that there are no spillover effects within the holding.

When we study how banks rebalance their portfolios after the shock, we find that holding-company banks do not reduce household loans to rebalance their portfolios, while independent banks need to reduce household loans in order to increase real estate loans and bond holdings during the recovery period. The evidence also shows an important result with respect to non-traditional banking activities (non-interest income activities). When the holding displays low liquidity, affected holding-company banks move resources from bonds and real estate loans to non-traditional activities. By contrast, when the holding displays high liquidity levels, affected subsidiaries increase real estate loans and bonds and decrease non-traditional activities. This evidence is in line with results shown in the bank stability literature; non-traditional activities have been shown to be an important determinant of systemic and individual risk at banks (see Brunnermeier et al., 2012, and Lepetit et al., 2008). Hence, the difference in risk between banks owned by holdings with high vs. low liquidity may be driven by their different engagement in non-traditional activities.

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

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

We contribute to the existing literature along several dimensions. Our first contribution is to the literature on multibank holding companies. This literature has studied the effect of holding company affiliation on lending (e.g., Houston et al., 1997), access to federal funds and CD markets (e.g., Campello, 2002), capital injections (Gilbert, 1991) and risk-based capital (Lambert et al., 2018). The closest paper to ours in this literature is Aschcraft (2008). Ashcraft studies the relationship between holding company affiliation and 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 at holding subsidiaries. We complement this literature by showing that when faced by the same exogenous shock, holding-company banks are more resilient than independent banks in terms of both individual and systemic risk. Hence, in addition to looking at individual bank risk, we also examine the *comovement* of bank risks after the shock. Furthermore, we also study how the differential effects on risk for independent and holding-company banks may take place. Specifically, we examine how these two types of banks rebalance their portfolios after being hit by the same 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 (e.g., Anginer et al., 2014). We study how holding company affiliation affects banks' risk resiliency in terms of individual and systemic risks. To the best of our knowledge, this is the first paper to study this relationship.

Our work is also related to the literature studying the effects of natural disasters on bank behavior. This literature has focused on the effects on credit supply after the shock.

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

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

The remainder of the paper is structured as follows. The next section provides background information about the 2005 hurricane season. Section 3 describes our data, the treatment identification, and the definition of our main variables. Section 4 describes our empirical strategy. Section 5 presents the main results. Section 6 explores the dynamics behind the results. Section 7 concludes.

2 Background on the 2005 hurricane season

Hurricanes Katrina, Rita and Wilma, which formed the bulk of the 2005 Atlantic hurricane season, made landfall in the US Gulf Coast in close succession between August 25 and

October 27, 2005. Collectively, these three weather systems inflicted the largest recorded damage in US history: US $162.5 billion. The largest chunk of the damage was caused by Katrina ($125 billion), followed by hurricanes Wilma ($19 billion) and Rita ($18.5 billion) (National Hurricane Center, 2018). Hurricane Katrina affected Alabama, Florida, Louisiana, Mississippi, and parts of Arkansas, with the heaviest impact in Louisiana and Mississippi. Hurricane Rita affected Louisiana and parts of Texas, while Wilma affected mostly southern Florida. The hurricanes put strain on banking operations, insurance companies, businesses and individuals alike. The geographic dispersion of damage across multiple states, together with repeated hits to Louisiana, made the scale of damage unprecedented; compounding the Louisiana wind damage was also heavy flooding in New Orleans, which put large parts of the city under water. 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 owned or mortgaged by banks, which increased bank losses and deflated their balance sheets.

Specifically, the hurricane season reduced banks' net equity by destroying the collateral on outstanding mortgage loans, thereby leaving banks exposed to defaults not covered by assets.[3] This, in turn, increased their losses given default independent of the default rates, which also rose after the hurricanes. With the insurance sector covering significantly fewer hurricane claims than expected, thousands of homeowners were left without homes and insurance payouts, affecting their ability to service their mortgages.[4] The resultant loss of physical assets increased bank mortgage losses, and the share of non-performing loans grew. This is displayed in Figure 1, showing the non-performing loan ratios for the affected and the control banks in our sample.[5]

Figure 1 shows a clear downward trend in non-performing loans for both 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

[3]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).

[4]For a discussion of the insurance problems after the 2005 hurricanes, see Section 2 of Raykov (2015). There were multiple controversies as to whether wind-driven water damage should be covered under hurricane policies, which insurers interpreted as pure wind insurance.

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

made landfall. For the next ten months, affected banks display a notably higher fraction of non-performing loans than control banks, with the two groups converging approximately twelve months after the shock, consistent with Cortés and Strahan's (2017) estimate of the duration of the hurricanes' economic effect. Towards the end of the sample period, non-performing loans for both control and affected banks start trending back to their 2004 levels, reflecting the gradual buildup of risk leading to the 2007-2008 crisis. Overall, the disparity between loan performance at affected and control banks, its duration and timing are fully consistent with prior research on the 2005 hurricane season.

3 Data

We combine data from multiple sources to study the effect of the 2005 hurricanes on bank risk. We use daily stock return data from Bloomberg to compute quarterly systemic risk measures (MES and, for robustness, SRISK) for publicly traded US commercial banks. We merge these measures with quarterly balance sheet and income statement variables from the banks' Reports of Condition and Income. We also use the Bloomberg returns data to compute measures of individual bank risk (market Z-Scores), obtaining a quarterly panel. To identify banks belonging to multibank holding companies, we use information from Bloomberg on the name of the ultimate parent of each institution. We identify a bank as independent if the bank does not have a parent company. We obtain balance sheet information about bank holding companies from their respective FR-Y9C reports. We limit the sample period to six years (2002-2007) to avoid overlap with the financial crisis starting in 2008. A full description of the variables and their sources is given in Appendix A.

3.1 Treatment definition

Since the main impact of the hurricane season on banks occurred through the destruction of mortgage collateral, we use each bank's mortgage lending to disaster counties before the shock as an exposure metric for its hurricane-related losses. Mortgage markets are more relevant for our study than bank deposit markets because hurricanes do not have an unambiguous impact on deposits (Federal Deposit Insurance Corporation, 2005; Chavaz, 2016), whereas they unambiguously destroy mortgaged homes.[6]

[6]Regarding the correlation between deposit and lending markets, see Petersen and Rajan (2002).

We define a continuous treatment measure, *Exposure*, to identify the affected banks. For each bank, *Exposure* equals the fraction of mortgage lending it extended between 2002 and 2004 to FEMA-designated disaster counties for the hurricanes Katrina, Rita and Wilma. We obtain the locations of mortgaged properties and the amount of each loan from the HMDA data files. Banks that did not lend to affected areas during the pre-hurricane period and thus have an *Exposure* equal to zero are the control group in our setting.

We identify the disaster counties as those officially designated by FEMA for individual disaster assistance as September 28, 2005 (for hurricanes Katrina and Rita) and November 8 (for hurricane Wilma).[7] To eliminate banks lending to counties whose treatment status is uncertain, we exclude banks that had lending exposure to public-assistance-only counties (which generally sustained lesser damage) and were not exposed to individual-assistance counties.

The final selection of treated counties from the 2005 hurricane season is shown in red in Figure 2. In this figure, a bank is defined as treated if it had positive mortgage lending to a treated county during 2002-2004 (that is, if *Exposure* is larger than zero). Banks without mortgage loan exposure to a treated (red) county, but with an exposure to an excluded (beige) county receiving only public assistance, are dropped from the sample.

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

Table 1 lists the number of bank-quarter observations for our sample (bank-years from 2002 to 2007) across treated and control groups, and across independent vs. holding-company banks. Table 2 provides summary statistics for our sample. Our sample includes both local (state and county) banks, as well as big multistate banks. For all banks, exposures to the hurricane are prorated according to their mortgage lending to the affected counties.

[7]FEMA offers two types of disaster assistance: individual assistance and public assistance (Federal Emergency Management Agency, 2015). Counties with individual assistance are those with damage to residential homes, which makes their owners eligible. By contrast, public assistance is meant to repair public infrastructure only. In many public-assistance areas, such as East Arkansas, assistance was limited to removing debris, reconnecting power lines, or clearing roads, with little damage to individual homes.

3.2 Risk measures: Z-Score and MES

To gage the individual and systemic impact of the shock, we construct both systemic and individual measures of bank risk. We use marginal expected shortfall, or MES, (Acharya et al., 2017) to measure systemic risk, whereas at the individual bank level, we use market Z-Scores. Although our results are consistent across both metrics, they do not measure the same thing.

MES measures the expected capital shortfall of an individual bank i, conditional on the rest of the financial system experiencing distress. It captures the comovement between the individual bank and the rest of the financial system, rather than a bank's absolute level of risk. Therefore, we use MES to capture the system-wide effect of the hurricane shock.

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, $P_{i,d}$ is the share price, and $s_{i,d}$ is its relative number of shares outstanding, then this bank's MES for quarter t is defined as

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

and

$$Index_{i,d} = \sum_{j \neq i} s_{j,d} P_{j,d}, \quad \text{where} \quad s_{j,d} = \frac{\text{Shares outstanding}_{j,d}}{\sum_{j \neq i} \text{Shares outstanding}_{j,d}}. \tag{2}$$

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 as 1 plus the bank's average daily return over the quarter, divided by the quarterly standard deviation of the bank's return:

$$\text{Z-Score}_{i,t} = \frac{1 + \mathbb{E}R_{i,d}}{\sigma_{R_{i,d}}}. \tag{3}$$

These two metrics provide information about both the absolute level of risk attained by each bank and its comovement with other affected banks after the shock. We provide descriptive statistics for these risk measures in Table 2.

4 Empirical strategy

To analyze the role of holding companies in shaping the effect of a negative shock on bank risk, we estimate variations of the following panel data model:

$$\begin{aligned} y_{it} = \alpha_0 + \sum_i \alpha_{1,i} d_i + \alpha_2 Post_t + \beta_1 Exposure_i * Post_t + \beta_2 Post_t * Independent_i \\ + \beta_3 Exposure_i * Post_t * Independent_i + \sum_k \gamma_k X_{k,i,t} + \epsilon_{it}, \end{aligned} \tag{4}$$

where y_{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. We exclude the crisis period to avoid biases arising from changes in bank behavior. However, our main results regarding the role of holding company affiliation are robust to longer time periods.

The variable $Exposure_i$ is a continuous bank-level variable ranging from 0 to 1, defined as the bank's mortgage lending share to affected counties during the the three years preceding 2005. Our setting is a difference-in-difference approach; thus, the coefficient β_1 in equation (4) captures the differential effect for the banks hit by the shock (i.e., exposed banks) over banks that were not hit (i.e., control banks).

We are interested in the role that being part of a holding company has on bank risk. Therefore, we further interact the fourth term in (4) with a dummy variable indicating whether the bank is independent, $Independent_i$. We define a bank as independent if it does not have a parent bank according to the Bloomberg database. Our coefficient of interest is then β_3, which captures the differential effect on affected independent banks over affected holding-company banks.

We also include bank fixed effects d_i in all models to control for time-invariant unobserved characteristics.[8] 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. Including covariates that are likely to be affected themselves

[8]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 $Independent_i * Exposure_i$.

can lead to biases in the coefficient of interest (Angrist and Pischke, 2009). In a set of robustness tests, we include bank controls that are commonly used in the bank stability literature (e.g., Brunnermeier et al., 2012). These controls are the logarithm of the assets, leverage, return on assets (ROA), non-interest income as a share of total income, and loan (quarterly) growth.

The identification of causal effects in our difference-in-difference strategy rests on two key assumptions: that there are parallel trends for affected and control groups; and that the treatment assignment is uncorrelated with changes in the outcomes of interest. We take these assumptions as valid for now and discuss their validity in our setting in Section 5.2.

5 Results

5.1 Main results

We explore the effect of a negative shock to bank balance sheets on bank risk. The results of our panel data model are shown in Table 3. We first study the effect of the shock on individual and systemic risk without taking into account the role of holding affiliation. Results for these models are presented in columns (1) and (2) in this table. The *Post* dummy enters with a positive sign and is statistically significant in the model in column (1). This suggests that on average, insolvency risk decreased for all banks after the second half of 2005. We do not find any significant effect of the negative shock on the individual risk for affected banks relative to control banks in this column. This is shown by the coefficient of the interaction term of the *Post* and *Exposure* variables, which is not significant. The model for systemic risk displays similar results. Column (2) likewise does not show any significant effect of the negative shock on the MES for affected banks relative to control banks. These results are puzzling because one would expect a big negative shock to bank balance sheets to have an impact on their risk. In particular, one would expect an increase in insolvency risk, driven by the large credit losses experienced by banks after the disaster.[9] 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

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

that increase their correlatedness with the other banks in the system.

These puzzling findings suggest that the aggregate effect might be masking heterogeneity based on bank types. In this regard, 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. Thus, stability at these two types of banks is also likely to differ. In principle, the effect of holding company affiliation on risk could be either positive or negative. For example, parents can support subsidiaries facing adverse shocks via internal capital markets (e.g., Gilbert, 1991), thereby reducing insolvency risk at affected banks. Moreover, even if parent banks do not channel funds to subsidiaries, the perception of an implicit guarantee of support may lead to a lower share price volatility of the subsidiary. However, holding affiliation can also lead to an increase in risks via higher risk-taking (e.g., Hughes et al., 1996) or via contagion from other banks in the same holding (e.g., Berrospide et al., 2016). Regardless of how the shock affects independent banks, the impact likely differs for holding-company banks. If the sign of 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 bank risk, as shown by the negative sign of the triple interaction term in the model in column (3). The coefficient equals -47.59 and is significant at the 5% level. The effect is also economically significant; a 10-percentage-point increase in an independent bank's exposure leads to a decrease in its Z-Score of 4.7, or 0.14 (4.7/34.6) standard deviations. The evidence for holding-company banks suggests that they are not significantly affected by the negative shock, as can be seen in the interaction term of the *Post* and *Exposure* variables in this model. The coefficient equals 27.67, but is not statistically significant. A decrease in Z-Score implies an increase in insolvency risk; hence, our results suggest that independent banks face increased insolvency risk after the shock, while the insolvency risk of holding affiliates is unaffected.

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

The results in this section show that banks that are part of a holding company are more resilient to shocks than independent banks, consistent with internal capital markets playing a role within the holding or with implicit guarantees affecting the market perception of bank stability. In Section 6.1 we examine in more detail whether holding company characteristics exacerbate or mitigate the resiliency of holding affiliates. Before doing that, we present additional evidence that our main results are robust.

5.2 Robustness

In this section, we 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 2002-2004 (i.e., banks with $Exposure > 0$).

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

5.2.1 Parallel trends

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

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

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

5.2.2 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. In order to show that this is the case, we first control for time-varying characteristics commonly used in the bank stability literature, in columns (3) and (4) of Table 4. The evidence from these models shows that our results remain unchanged when controlling for the above covariates. Therefore, the results presented above are not driven by omitted observable characteristics. Among the controls added, size, as proxied by the logarithm of assets, shows to be positively related with systemic risk, in line with results found in previous literature (e.g., Laeven et al., 2016).

Second, we test the robustness of our results using propensity score matching to match treated banks to similar banks from the control group. To this end, we match banks according to size, holding company affiliation and by state, using four years of pre-shock data. We present the summary statistics of the matched sample in the last five columns of Table 2. We show the statistics for the full sample and for independent versus holding-company banks. The last column in the table shows that the treated and control group display similar characteristics after the matching. We estimate our model using the matched sample in the last two columns of Table 4; our results continue to hold. Thus, imbalances between control and treated banks do not explain our results.

Finally, one remaining concern is that independent banks might be more exposed to affected coastal regions than holding-company banks. To account for this concern, in unreported regressions we include county-year fixed effects to compare the different bank types within the same county. Our results remain unchanged when controlling for this.

5.2.3 Other robustness tests

Holding-company-owned banks may be more geographically diversified than independent banks, which could also explain the higher resiliency of holding affiliates. Therefore, we additionally explore whether the differential effect of the shock on independent banks captures the effect of geographic diversification instead of holding company affiliation. We test whether this is the case by computing a geographic concentration index, HHI_{div}, defined at the bank level as the Herfindahl index of mortgage loans across counties.[10] A higher HHI_{div} implies higher geographic concentration and, thus, lower geographic diversification in lending. We show the results of this test in Table 5. In the first two columns, we replace the holding company affiliation dummy by the bank geographic diversification measure, HHI_{div}. The simple interaction term capturing the effect of the shock on risk suggests that individual and systemic risk both increased after the shock as expected, as indicated by the models in columns (1) and (2). The results also suggest that less-diversified banks lending to affected areas before the shock also display higher insolvency risk, as suggested by the negative and significant coefficient of the interaction term $Exposure * HHI_{div}$ in model (1). The triple interaction term, however, is not significant in this model, suggesting that geographic diversification neither exacerbates nor mitigates the effect of the negative shock on bank risk.

In the last two columns, we include both triple interactions ($Post * Independent *$

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

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

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

$$SRISK_{it} = W_{it} \left[kLVG_{it} + (1-k)LRMES_{it} - 1 \right], \tag{5}$$

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

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

6 Understanding holding-company banks' resiliency

6.1 Holding company dynamics

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

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

In our second set of tests, we study spillover effects to other banks in the holding. The literature on holding-company banks argues that given a negative shock, internal capital market operations within the holding affect investments across several markets, rather than concentrating on the affected market only (e.g., Berrospide et al., 2016). This literature argues that when relative profitability changes, banks either move resources from one market to another, or cut investments in all markets in response to a single-market shock. In either case, one would expect to see an effect on the risk of unaffected holding company members. Next we test whether this is the case.

6.1.1 Holding-company banks and holding liquidity

We first examine whether resiliency depends on the holding's cash and equity, calculated as a share of assets. For this, we estimate our model on the holding-company banks only, and include a triple interaction between the *Post* and the *Exposure* variables with the holding's cash or equity level. Table 6 shows the estimation results from these models. The first two columns study the effect of the holding's cash (as a share of assets) on the Z-Score and MES metrics, respectively. The estimate of the interaction of the *Post* and the *Exposure* variable is now negative and significant at the 5% level in column (1), whereas the triple interaction term is positive and significant at the 5% level. This result indicates that individual insolvency risk increases for shocked holding affiliates, but this negative effect is reversed as the cash of the holding increases. In particular, a 10-percentage-point increase in the cash of the holding (as a share of assets) leads to an increase of 20.8 in Z-Score.

Results for the MES are in line with the evidence for the Z-Score. The simple interaction estimate in column (2) is positive and significant at the 5% level, whereas the estimate of the triple interaction term is negative and significant at the 5% level. These estimates suggest that systemic risk increases when holding-company banks are affected by a shock, but this is also reversed as the cash of the holding increases. In particular, a 10-percentage-point increase in the holding's cash as a share of assets reduces MES by 0.05.

The last two columns in this table study the role of the holding's equity on the Z-Score and MES, respectively. We do not find any significant heterogenous effect of the holding's equity on either MES or Z-Score, as shown by the insignificant coefficients of the triple interaction term in these models. Therefore, holding equity does not have a differential effect on the risk of subsidiaries faced by a negative shock. The interaction term of *Exposure* and *Equity* shows a positive and significant coefficient in column (3). This suggests that affected banks owned by holdings with higher equity levels display lower insolvency risk. This relation is only weakly significant in the systemic risk model in column (4).

6.1.2 Spillover effects to other banks in the group

We now study whether unaffected banks that are part of a holding company with at least one other affected bank display an increase in insolvency or systemic risk. The dummy *Group exposed* equals 1 if bank i is unaffected, while at least one other bank in the same holding is. Table 7 presents the results for these models.

It has been argued that cross-market spillover effects exist in the lending of banks operating in multiple markets (e.g., Berrospide et al. 2016). However, the interaction terms in both models (Z-Score and MES) are not significant in columns (1) and (2). These results show that there is no increase in risk for unaffected banks in affected holdings after the shock: they do not suffer risk externalities caused by affected banks.

The evidence in this section thus suggests two main findings: that the liquidity of the holding company plays a role in shaping the resiliency of holding-company banks; and that there is no evidence of spillover effects across banks in the same holding.

6.2 Portfolio rebalancing

The 2005 hurricane season resulted in a significant reallocation of financial resources, including price effects on the corporate bond markets (Massa and Zhang, 2011), increased mortgage lending demand during the rebuilding (Cortés and Strahan, 2017), deposit inflows of government aid and insurance, as well as deposit outflows to meet emergency expenses (Federal Deposit Insurance Corporation, 2005). The relative profitability of different assets changed, so many banks chose to rebalance their portfolios.

In this section, we study how independent and holding-company banks rebalance their asset portfolios after the shock, and analyze whether the rebalancing activity of holding-company banks depends on the holding's cash levels.

Table 8 displays the results for independent banks. Results in this table show that both affected and unaffected independent banks rebalanced their portfolios after the shock, albeit to a different extent. In particular, as shown by the *Post* dummy in columns (5) and (6), they decreased household loans and increased real estate loans to be able to meet the higher real estate loan demand in the rebuilding phase. This behavior is consistent with the lack of access to internal capital markets, which typifies independent banks and necessitates a reallocation of the existing resources. However, affected independent banks decreased household loans by a larger amount and increased real estate loans by more than the unaffected banks did. Bond holdings decreased for unaffected banks and increased for affected banks after the shock; we conjecture that the increase in bond holdings for affected banks could be due to flight-to-quality motives.[11] We do not find any significant effect for securities holdings, assets sold, and non-interest income in columns (1), (2) and (4), respectively.

We present the corresponding results for holding-company banks in Table 9. Previously we showed that the cash of the holding plays an important role in shaping the subsidiaries' stability. Therefore, for each asset class, we first look at the effect of the shock on the asset share, without accounting for the role of the holding's cash assets. (This is reflected in the odd-numbered columns of Table 9.) We then allow for heterogeneous effects of the holding cash level on asset rebalancing, shown in the even-numbered columns.

If we ignore the heterogeneous effect of the holding's cash level on its subsidiaries, we observe an increase in non-interest income and real estate loans for affected holding-company banks after the shock. This is shown by the positive and significant estimate of the interaction term in columns (7) and (9). Household loans are reduced by both affected and unaffected holding-company banks after the shock, ignoring for holding characteristics (shown by the negative and significant sign of the *Post* dummy in column (11)). None of the other assets appear to have a significant change after the shock.

When we allow for heterogeneous effects of the holding's cash level on the rebalancing of assets, we observe in columns (6) and (10) that banks whose holdings have lower cash

[11]Lambert et al. (2018) find a similar result. They show that affected independent banks increase government securities and decrease loans to non-financial firms.

assets tend to reduce bond holdings and real estate loans (this finding is weakly significant), whereas increasing securities held and their involvement in higher-risk non-interest income activities, as shown in columns (2) and (8) of the same table. By contrast, banks whose holdings have significant cash assets display the opposite behavior: they increase their bond holdings and real estate loans, while decreasing non-interest income activities. We do not observe any significant effect on household loans when controlling for holding cash assets.

Thus, the evidence in this section shows that holding-company banks do not reduce household loans to rebalance their portfolios when we account for heterogeneous effects of holding liquidity, while independent banks need to reduce these loans in order to increase real estate loans and bond holdings in meeting higher mortgage demand after the shock. This fact is important for hurricane recovery because counties with a higher presence of independent banks could take longer to recover under reduced household lending. Furthermore, the evidence shows an important result with respect to non-traditional activities, here proxied by non-interest income over total income. Banks from less-liquid holdings move resources away from bonds and real estate loans towards (riskier) non-traditional activities; and banks from more-liquid holdings increase bonds held and real estate loans and decrease non-traditional activities instead. This evidence is in line with the literature and with our results from the previous sections; non-traditional activities have been shown to be an important determinant of systemic and individual risk at banks (Brunnermeier et al., 2012; Lepetit et al., 2008). Hence, the difference in risks between holding-company banks owned by more- vs. less-liquid holdings may be driven by their different involvement in non-traditional activities.

7 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 and use an exogenous shock to bank balance sheets to study the net effect of holding company affiliation on bank stability.

We show that holding-company banks are more stable than independent banks when affected by a negative shock. They display lower systemic risk levels, as measured by the MES and SRISK metrics, and lower individual risk levels, as measured by market Z-Scores. Furthermore, we show evidence that the cash of the holding plays a role in shaping their resiliency, consistent with an internal capital market story.

We also show how banks rebalance their portfolios after the shock. As the cash of the holding increases, holding-company banks transfer resources away from non-traditional banking activities and increase real estate loans and bond holdings. The decrease in non-traditional banking activities is consistent with the increased stability of these banks, as suggested by previous literature.

In a broader context, we complement the literature on multibank holding companies. Researchers have studied the relationship between holding affiliation and CAMEL ratings (Ashcraft, 2008), and holding company affiliation and risk-based capital (Lambert et al., 2018). We complement this literature by showing that, when faced by the same exogenous shock, holding-company banks are more resilient than independent banks. Our paper also sheds light on the holding's role in restoring stability and the potential dynamics behind it.

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

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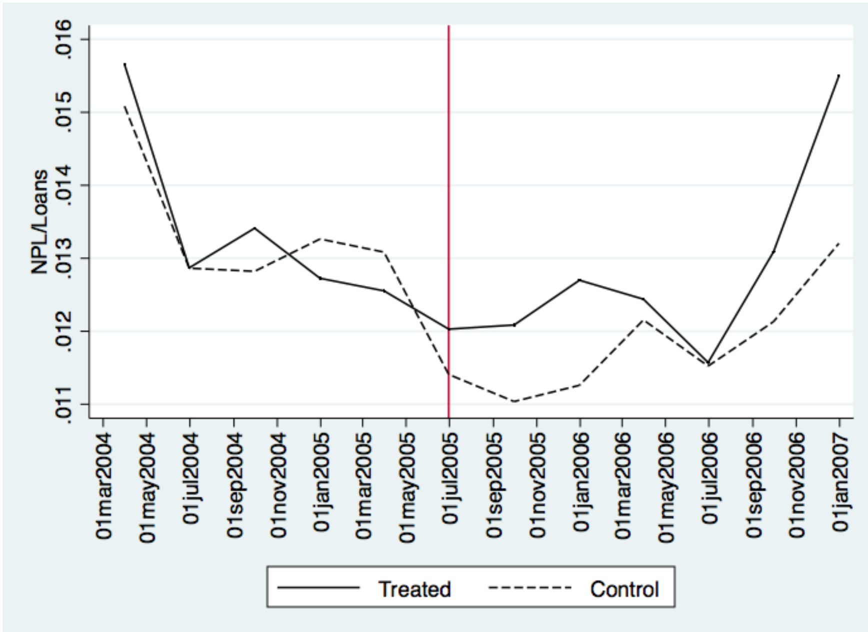
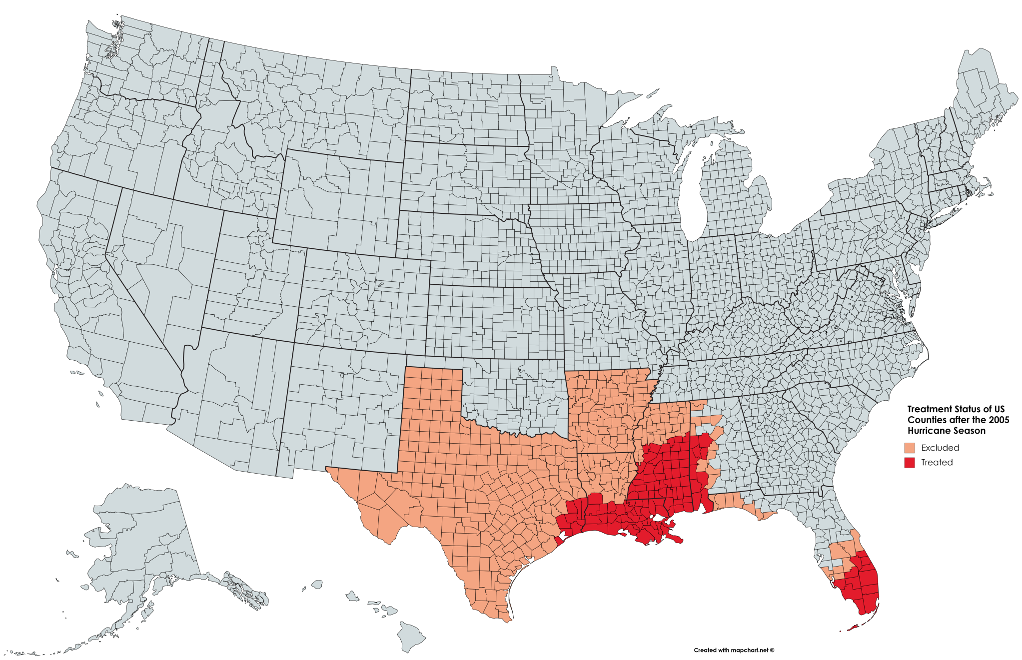
Figures

Figure 1. Evolution of Non-Performing Loans



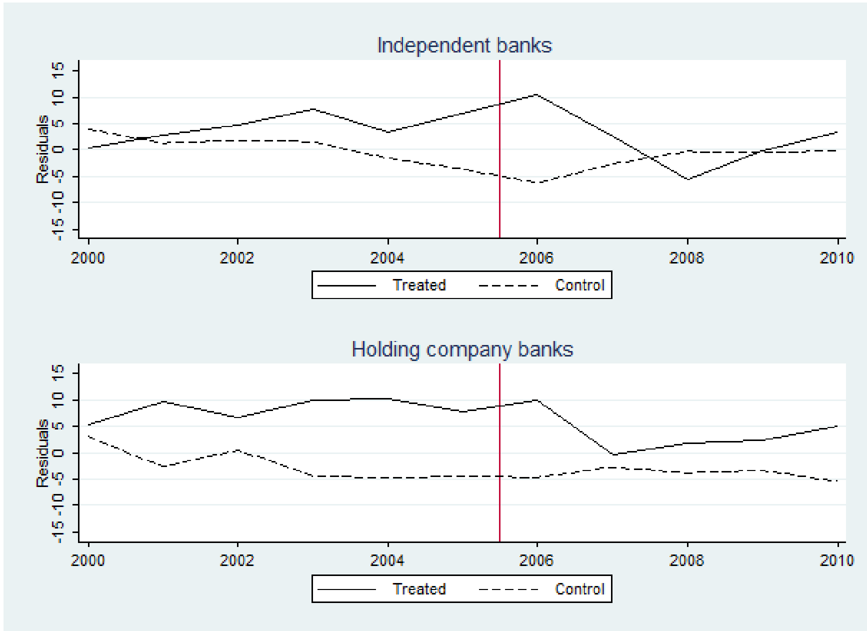
Evolution of non-performing loans as a share of total loans for treated and control banks over time. A bank is defined as treated if it had positive mortgage lending to a treated county during 2002-2004. Untreated banks with exposure to an excluded county are dropped.

Figure 2. Affected, Control and Excluded Areas



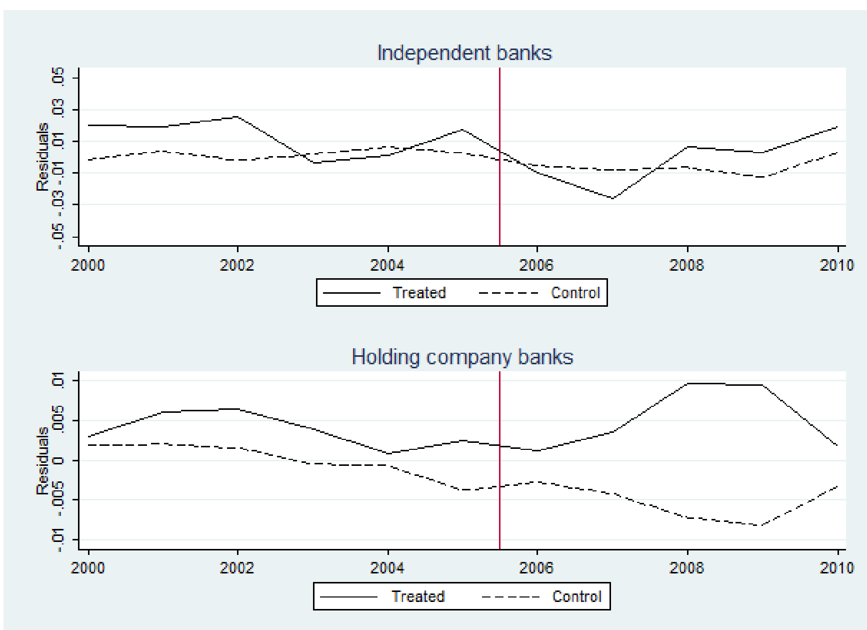
Counties affected by hurricanes Katrina, Rita and Wilma (in red), excluded counties (in beige), and control counties (in grey). A bank is defined as treated if it had positive mortgage lending to a treated county during 2002-2004. Untreated banks with exposure to an excluded county are dropped.

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 a treated county during 2002-2004. Untreated banks with exposure to an excluded county are dropped.

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 a treated county during 2002-2004 and defined as independent if the bank does not have a parent bank according to Bloomberg.

Tables

Table 1: Distribution of Treated and Control Banks

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

Number of bank-quarter observations for our sample (bank-years from 2002 to 2007) across treated and control groups, and independent versus holding-company banks. A bank is defined as treated if it had positive mortgage lending to a treated county during 2002-2004.

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										
Z-Score	55.98	33.94	64.47	27.98	-0.272	50.37	34.76	51.38	31.07	-0.030
MES	0.00035	0.031	0.009	0.018	-0.349	-0.0001	0.029	0 .001	0.024	-0.053
Log(assets)	12.27	1.102	14.04	1.907	-1.137	12.02	1.084	12.03	1.085	-0.017
Leverage	0.892	0.045	0.906	0.018	-0.429	0.899	0.035	0.903	0.030	-0.108
ROA	0.003	0.006	0.006	0.004	-0.379	0.005	0.006	0.004	0.008	0.170
Non-interest/Income	0.803	0.807	1.263	1.034	-0.494	0.664	0.856	0.897	1.252	-0.216
Loan growth	1.058	0.087	1.042	0.065	0.197	1.041	0.072	1.057	0.088	-0.196
Panel B: Independent banks										
Z-Score	49.54	35.17	54.61	28.42	-0.158	50.86	35.231	51.26	31.86	-0.011
MES	-0.0005	0.038	0.005	0 .021	-0.182	0.0003	0.029	0.0007	0.024	-0.017
Log(assets)	11.74	1.038	12.68	1.748	-0.650	12.04	1.078	12.05	1.078	-0.011
Leverage	0.896	0.037	0.909	0.026	-0.395	0.900	0.033	0.905	0.026	-0.149
ROA	0.005	0.006	0.005	0.006	-0.070	0.005	0.006	0.005	0.007	0.116
Non-interest/Income	0.698	0.891	1.099	1.245	-0.370	0.673	0.848	0.882	1.178	-0.203
Loan growth	1.043	0.073	1.039	0.075	0.051	1.036	0.067	1.05	0.083	-0.180
Panel C: Holding-company banks										
Z-Score	50.18	29.51	59.68	27.215	-0.334	43.92	27.38	52.22	25.02	-0.316
MES	0.001	0.027	0.009	0.019	-0.329	-0.007	0.025	0.004	0.022	-0.492
Log(assets)	12.06	1.336	14.23	1.991	-1.278	11.5	1.075	11.81	1.161	-0.278
Leverage	0.900	0.035	0.914	0.025	-0.465	0.870	0.058	0.873	0.050	-0.058
ROA	0.004	0.007	0.006	0.005	-0.277	-0.0002	0.008	-0.004	0.010	0.492
Non-interest/Income	0.791	0.921	1.077	0.798	-0.331	0.482	1.004	1.088	1.967	-0.387
Loan growth	1.051	0.084	1.045	0.072	0.074	1.133	0.108	1.142	0.114	-0.075

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 bank in Panel B; and for treated and control holding-company banks in Panel C. A bank is defined as treated if it had positive mortgage lending to a treated county during 2002-2004 and defined as independent if the bank does not have a parent bank according to Bloomberg. The full samples are presented on the left side of each panel and the matched samples on the right. The normalized difference in means are also displayed. Definitions and sources of control variables are listed in Appendix A.

Table 3: Bank Risk

	Z-Score (1)	MES (2)	Z-Score (3)	MES (4)
Post	9.978***	0.00173	8.885***	0.00352*
	(1.602)	(0.00121)	(2.219)	(0.00195)
Post*Exposure	-15.96	0.0157	27.67	-0.0335*
	(11.65)	(0.0130)	(16.82)	(0.0177)
Post*Independent			1.483	-0.00265
			(3.129)	(0.00251)
Post*Exposure*Independent			-47.59**	0.0539**
			(20.11)	(0.0232)
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 to 2007. All regressions are estimated with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 4: Robustness

	Placebo test		Bank controls		Matched sample	
	Z-Score	MES	Z-Score	MES	Z-Score	MES
	(1)	(2)	(3)	(4)	(5)	(6)
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
			(2.844)	(0.00213)	(3.331)	(0.00460)
Post*Exposure			37.70*	-0.0235	61.20***	-0.00485
			(19.58)	(0.0161)	(19.79)	(0.0280)
Post*Independent			2.337	-0.00254	6.617	-0.00358
			(3.280)	(0.00253)	(4.418)	(0.00522)
Post*Independent*Exposure			-59.22***	0.0406**	-50.31**	0.0673**
			(22.27)	(0.0194)	(20.92)	(0.0284)
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)		
Observations	2,253	1,681	2,931	2,225	1,099	810
R-squared	0.048	0.003	0.024	0.013	0.025	0.025

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

Table 5: Geographic Diversification

	Z-Score (1)	MES (2)	Z-Score (3)	MES (4)
Post	8.122**	0.00511	6.559	0.00792*
	(3.336)	(0.00376)	(4.568)	(0.00456)
Post*Exposure	-49.69***	0.0419*	11.23	-0.0106
	(17.28)	(0.0247)	(27.73)	(0.0248)
Post*Independent			1.944	-0.00346
			(3.307)	(0.00262)
Post*Independent*Exposure			-51.86***	0.0464***
			(19.45)	(0.0161)
HHI_{div}	7.856	0.00382	7.858	0.00400
	(5.909)	(0.00769)	(5.936)	(0.00767)
Exposure*HHI_{div}	-182.9***	-0.0686	-164.8***	-0.0819*
	(37.80)	(0.0543)	(48.29)	(0.0463)
Post*HHI_{div}	1.905	-0.00490	2.155	-0.00576
	(5.288)	(0.00485)	(5.703)	(0.00506)
Post*HHI_{div} *Exposure	42.37*	-0.0345	24.71	-0.0209
	(22.91)	(0.0329)	(30.58)	(0.0244)
Observations	2,928	2,259	2,928	2,259
R-squared	0.029	0.009	0.030	0.011

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

Table 6: holding-company banks and the Role of the Holding

	Z-Score (1)	MES (2)	Z-Score (3)	MES (4)
Post	4.870	0.00489	6.306	0.0251*
	(6.297)	(0.00549)	(18.69)	(0.0127)
Post*Exposure	-404.5**	0.380**	123.4	-0.127
	(198.6)	(0.161)	(101.7)	(0.138)
Cash/TA$_{Holding}$	-257.5**	-0.0598		
	(108.6)	(0.126)		
Exposure*Cash/TA$_{Holding}$	-3,657	1.330		
	(2,251)	(2.797)		
Post*Cash/TA$_{Holding}$	75.98	-0.00942		
	(196.4)	(0.174)		
Post *Exposure*Cash/TA$_{Holding}$	16,036**	-16.03**		
	(7,598)	(6.179)		
Equity/TA$_{Holding}$			-199.2	0.161
			(206.7)	(0.154)
Exposure*Equity/TA$_{Holding}$			2,528***	-1.300*
			(876.7)	(0.682)
Post*Equity/TA$_{Holding}$			34.83	-0.226*
			(217.1)	(0.130)
Post*Exposure*Equity/TA$_{Holding}$			-1,186	1.029
			(980.2)	(1.199)
Observations	797	691	797	691
R-squared	0.049	0.018	0.039	0.018

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. $Cash/TA_{Holding}$ corresponds to the holding cash level over assets and $Equity/TA_{Holding}$ corresponds to the holding equity over assets. The sample period spans from 2002 to 2007. All regressions are estimated with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 7: Spillover Effects Within Holdings

	Z-Score	MES
	(1)	(2)
Post	8.615***	0.00743**
	(2.821)	(0.00288)
Post*Group exposed	-5.140	-0.00476
	(3.961)	(0.00597)
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. *Group exposed* equals one for unaffected banks that are part of a group where at least one bank is affected. The sample period spans from 2002 to 2007. All regressions are estimated with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 8: Independent Banks' Portfolio Rebalancing

	Securities	Assets sold	Bonds	Non-interest income	RE loans	HH loans
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.000140	0.000310	-0.0157***	-0.0710	0.0264***	-0.00958***
	(0.000106)	(0.000225)	(0.00360)	(0.0506)	(0.00613)	(0.00258)
Post*Exposure	-0.000178	-0.000396	0.0381***	-0.106	0.0996**	-0.0465***
	(0.000139)	(0.000289)	(0.0137)	(0.159)	(0.0396)	(0.0157)
Observations	3,005	3,005	3,005	3,005	3,005	3,005
R-squared	0.007	0.006	0.048	0.004	0.106	0.100

This table presents the results of regressions studying the effects of the hurricane season on the portfolios of independent banks. The dependent variable name is shown in each column. *Securities* are securities over total assets. *Assets sold* are assets sold over total assets. *Bonds* are bonds over total assets. *Non-interest income* is non-interest income over total income. *RE loans* are real estate loans over total loans. *HH loans* is household loans over total loans. *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. The sample period spans from 2002 to 2007. All regressions are estimated with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 9: Holding-company banks' Portfolio Rebalancing

	Securities	Securities	Assets sold	Assets sold	Bonds	Bonds	Non-interest income	Non-interest income	RE loans	RE loans	HH loans	HH loans
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post	0.000215	0.00110	-0.000526	0.000918	-0.00727	-0.00942	-0.0982	0.113	0.0408***	0.0307	-0.0196***	-0.0149
	(0.000457)	(0.00121)	(0.000493)	(0.00156)	(0.00584)	(0.0166)	(0.0648)	(0.131)	(0.00724)	(0.0189)	(0.00323)	(0.0110)
Post*Exposure	-0.00119	0.0158*	-0.000696	0.0347	0.0154	-0.232**	2.497***	15.92***	0.126***	-0.229*	0.00872	0.104
	(0.00120)	(0.00845)	(0.00168)	(0.0224)	(0.0130)	(0.107)	(0.462)	(3.414)	(0.0270)	(0.127)	(0.0128)	(0.159)
Cash/TA$_{Holding}$		0.00616		0.0556**		-0.105		6.738**		-0.133		0.101
		(0.00812)		(0.0258)		(0.209)		(2.732)		(0.238)		(0.144)
Exposure*Cash/TA$_{Holding}$		0.104		0.0767		-7.468***		82.56		-18.26***		0.642
		(0.110)		(0.256)		(2.214)		(62.29)		(2.009)		(1.782)
Post*Cash/TA$_{Holding}$		-0.0210		-0.0416		-0.115		-4.154		0.188		-0.218
		(0.0251)		(0.0442)		(0.357)		(3.762)		(0.526)		(0.445)
Post*Exposure*Cash/TA$_{Holding}$		-0.876*		-1.831		11.73**		-682.5***		15.29**		-4.757
		(0.458)		(1.157)		(5.723)		(182.6)		(7.024)		(8.355)
Observations	1,413	930	1,413	930	1,413	930	1,413	930	1,413	930	1,413	930
R-squared	0.003	0.017	0.009	0.059	0.011	0.058	0.090	0.253	0.216	0.295	0.180	0.192

This table presents the results of regressions studying the effects of the hurricane season on the portfolios of holding-company banks. The dependent variable name is shown in each column. *Securities* are securities over total assets. *Assets sold* are assets sold over total assets. *Bonds* are bonds over total assets. *Non-interest income* is non-interest income over total income. *RE loans* are real estate loans over total loans. *HH loans* is household loans over total loans. *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. $Cash/TA_{Holding}$ corresponds to the holding cash level over assets. The sample period spans from 2002 to 2007. All regressions are estimated with robust standard errors clustered at the bank level (in parentheses). ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Appendix A: Variable Definitions

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

Appendix B: Alternative Measure of Bank Risk

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

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