Journal of Forensic and Investigative Accounting
Volume 17: Issue 3, Special Issue 2025

Earnings Management Through Securitization in the Wake of Natural Disasters: A Study of Bank Holding Companies

Qiuhong Zhao[*]

Introduction

The Federal Reserve has been slow to talk about climate risks compared with central banks in other countries. That could be partly because the topic is more politically polarized in the United States than many other places, so talking about it exposes the Fed—which is meant to be politically independent—to accusations that it is straying into partisan territory.

New York Times Oct. 17, 2019

Climate risk and reduction in natural disaster insurance coverage affect lending behaviors of banks originating mortgages with high flood risk. This study examines the extent to which such lending behaviors affect earnings management activities. The frequency of multibillion-dollar natural disasters, such as hurricanes, adversely impacts the strength and stability of financial institutions. Wind and flood damage inflict cost on property owners, residents, insurance companies, and the broader community in coastal areas. If banks engage in earnings management activities (i.e*.,* manipulation) to overstate their financial strength in the face of disaster-related loan losses, capital markets and national confidence in financial institutions will potentially be eroded.

Several recent studies have investigated the consequences of climate risk on banks' behavior, although financial arguments assert that such risk, if idiosyncratic, might be diversified away. Maso et al. (2022) examines the association between loan loss provisioning (LLP) and disaster risk, finding that the greater the disaster risk, the more loan loss provisioning in the financial industry. Maso et al.'s findings are consistent with the argument that natural disasters reduce borrowers' ability to repay loans, thereby resulting in lower quality of banks' lending portfolios and more loan loss provisioning. However, empirical evidence on the effect of natural disasters on earning management activities is mixed. For example, Yang and Bai (2024) examines the effect of the 2005 US hurricane strikes on banks' earnings management behavior in terms of big bath earnings management through discretionary LLP. They document opportunistic "big bath" accounting through discretionary LLP for affected banks compared to control banks identified by propensity score matching. However, Wu et al. (2022) document that corporate earnings management activities have been impeded following natural disasters in the sample period of 1980 to 2017. Wu et al. (2022)'s findings are contradictory to "big bath" accounting practices but consistent with the rational expectations of executives and the external monitoring of stakeholders. Therefore, it is important to investigate and provide further evidence on the effects of natural disasters on earnings management activities though both securitization and discretionary LLP for bank holding companies, given their critical role in financial stability. Unlike Yang and Bai (2023), this study explores the effects of 17 major natural disasters earnings management activities through not only loan loss provisions but also securitization activities, thereby providing more generalized evidence on the effects of natural disasters on banks' earnings management behavior.

Ouazad and Kahn (2022) document the real effects of natural disasters on banks' securitization activities. Their finding that lenders are significantly more inclined to increase mortgage shares originated and securitized below conforming loan limits after a billion-dollar weather event is consistent with their argument that banks are incentivized to sell their worse flood risk to the two main securitizing agencies, given that the decline in flood insurance availability increases risk in mortgage lending in parts of the country. This study builds on and extends Ouazad and Kahn's findings. Specifically, this study focuses on the consequences of natural disasters on lenders' behavior, thereby providing insight into the types of earnings management

[*]The author is associate professor at Texas A&M University – Corpus Christi. The author would like to acknowledge the comments and suggestions from participants at the 2023 Sustainability, ESG and Accounting Implications for the Academy and the Profession Conference of American Accounting Association.

channels to which the Securities and Exchange Committee (SEC) might need to pay more attention, particularly when examining financial statements of banks that originate mortgages with high flood risk.

This study offers evidence that affected banks, unlike the control group, are more likely to engage in securitization earnings management following billion-dollar events, despite reduction of mortgage sizes in flood prone areas. Zhao (2019) documents the partial substitution role between securitization gains and discretionary LLP as discount rates regarding fair value estimates of retained interests. Consequently, managers use securitization gains and LLPs as partial substitutes and that earnings management from securitization gains grows at an increasing rate to substitute income increasing LLP management as the level of risk retention increases. This study documents that compared to the control group, affected banks appear not to change their behavior through loan loss estimates so as to manage earnings following billion-dollar events perhaps due to increased monitoring from stakeholders after natural disasters.

The findings of this study contribute to the literature on the consequences of natural disasters on lenders' behavior, thereby offering insight into the types of earnings management channels to which the SEC might need to pay more attention, particularly when examining financial statements of banks that originate mortgages with high flood risk.

Disaster Risk Literature Review

Several finance studies have provided evidence on the effects of disaster risk on bank lending. Cortés and Strahan (2017) note that banks reallocate capital to more prosperous local markets in the aftermath of disasters. Meisenzahl (2023) finds that potential borrowers residing in climate-affected regions were less likely to qualify for bank loans. Potential borrowers in these regions were deemed 'high risk' as banks decreased lending for home equity lines of credit (HELOCs) and commercial real estate (CRE). However, Meisenzahl also finds that bank lending to borrowers deemed 'low risk' in climate-affected regions increased.

Billings, Ryan, and Yan (2022) employ forward-looking measures of climate risk at the U.S. county level and find that banks with high exposure to climate risk are less likely to originate non-agency mortgages and to increase their liquid assets when natural disasters occur in the areas that they serve. Consistent with branch-located loan officers leveraging their local market knowledge, banks with larger deposit shares in climate-risk counties originate more small business loans in those counties.

Research Questions and Hypotheses Development

Wind and flood damage inflict cost on property owners, residents, insurance companies, and the broader community in coastal areas. If banks engage in earnings management activities (i.e., manipulation) to overstate their financial strength in the face of disaster-related loan losses, capital markets and national confidence in our financial institutions will be significantly eroded. Prior research has found that banks manage earnings and regulatory capital by using loan loss provision and realized gains or losses of available-for-sale securities and that these banks manage earnings using securitization gains (Beatty et al., 1995; Collins et al., 1995; Barth et al., 2017; Dechow et al., 2010). Banks in areas experiencing billion-dollar weather-related events might have greater incentives to manipulate earnings compared to banks located in unaffected areas. This study explores the indirect consequences of billion-dollar natural disasters on banks' earnings management activities.

Ouazad, and Kahn (2022) document the real effects of natural disasters on banks' securitization activities. Specifically, they find that after a billion-dollar event, lenders are significantly more likely to increase the share of mortgages originated and securitized below the conforming loan limit. In addition, the increase is larger in neighborhoods for which such a disaster is 'new news,' i.e., such a neighborhood does not have a long history of hurricanes, but the increase is lower where flood insurance is required. Ouazad and Kahn's findings are consistent with their argument that banks may have an incentive to sell their mortgages with worse flood risk to the two main government sponsored agencies because declining availability of flood insurance makes mortgage lending riskier in certain parts of the country. Lending agencies sponsored by the U.S. government have become insurers of last resort for mortgages in disaster-prone areas, even as the National Flood Insurance Program has declined in recent years. I contend that when climate risk is transferred, earnings management behavior is disguised through sale of securitized loans, given that the share of mortgages originating and securitized below the conforming limit increases. In other words, an increased share of mortgages might make such manipulation nearly undetectable. However, banks might take other actions to manage flood risk, such as issuing mortgages by requiring greater loan-to-value ratios, that is, to richer and higher credit quality borrowers for underinsured properties (Sastry 2022). In addition, banks might require flood insurance on properties located in Special Flood Hazard Areas as designated by the Federal Emergency Management Agency. Accordingly, my first hypothesis is:

***$H_{1(null)}$:** Affected banks' securitization earnings management does not differ from the control group following billion-dollar events.*

Recent research documents that housing located in flood zones in the United States is currently overvalued by a total of $43.8 billion. Besides earnings management through transferring loans to two main Government Sponsored Entities (GSEs), accrual-based earning management, that is, LLP management, is common for banks to attain desirable earnings targets (Beatty et al.,1995; Collins et al.,1995). According to Yang and Bai (2023), natural disasters may motivate banks to employ big bath accounting procedures, wherein future performance is artificially heightened through reporting losses in excess of actual losses. The information that banks experiencing billion-dollar events have about local borrowers' ability to repay loans exceeds that of banks in unaffected areas, allowing banks in affected areas to originate loans to more credible borrowers. The loan portfolio quality of these affected banks might not be lower than that of the control banks. Accordingly, my second hypothesis is:

***$H_{2(null)}$:** Affected banks' LLP management does not differ from the control group, following billion-dollar events.*

Research Design

I obtain information on natural disaster events from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) of the University of South Carolina. SHELDUS contains a historical record of the names, dates, and direct losses of the natural hazards at county level from 1960 to present. I restrict the list to major natural disasters that occurred from 1998 to 2008. Due to the size and geographic diversity of the United States, the country experiences a variety of different natural disasters on a frequent basis. Therefore, not all natural disasters generate the same level of economic and psychological impacts (Cavallo et al., 2013). I capture the impact on analyst forecasts of 17 major and severe natural events from 1998 to 2008, defined as disasters that last for less than 30 days and cause damages of at least at least USD 1 billion dollars, inflation adjusted based on year 2013 (Hsu et al., 2018; Barrot and Sauvagnat, 2016). To test my hypotheses, I estimate abnormal loan loss provision (LLP) and abnormal realized securities gains and losses (RSGL) and assume that all securitization gains are discretionary.

Measure of Discretionary LLP

Following the loan loss provision literature (Collins et al., 1995), I estimate non-discretionary LLP as a linear function of the lagged allowance and the lagged level of and current change in non-performing assets, scaling all variables by beginning-of-year total loans to capture the size of the loan portfolio. In addition, regulatory capital (LAG_TCAP), earnings before taxes, extraordinary items, loan loss provisions (EBP), and year fixed effects are included in the regression. Then, I compute the difference between reported LLP and non-discretionary LLP as discretionary LLP. Abnormal LLP is computed as discretionary LLP multiplied by –1, so a higher value of abnormal_LLP corresponds to higher income increasing management.

$$LLP = \beta_0 + \beta_1 BEGLLA + \beta_2 BEGNPL + \beta_3 CHNPL + \beta_4 EBP + \beta_5 LagTCAP + \text{year fixed indicators} + \varepsilon \quad (1)$$

Where: BEGLLA is the beginning annual loan loss allowance (BHCK3123) divided by beginning-of-year total loans (BHCK2122); BEGNPL is lagged non-performing assets (BHCK5525 + BHCK5526) divided by beginning-of-year total loans (BHCK2122); EBP is income before taxes, extraordinary items, and loan loss provisions in year t (BHCK4301 + BHCK4230) divided by the beginning of total assets (BHCK2170); LAG_TCAP is total risk-based capital ratio (bhck3792/BHCKA223) at the end of year t–1; LLP is the annual loan loss provision (BHCK4230) divided by beginning-of-year total loans (BHCK2122). (Codes in BHC Y9-C reports are reported in parentheses.)

Measure of Discretionary Realized Gains/Losses

Following the security realized gains/losses literature (i.e., Beatty, Ke, and Petroni, 2002), I estimate the nondiscretionary portion of realized gains/losses as a linear function of the natural logarithm of total assets and cumulative unrealized gains and losses on AFS securities. Year fixed effects are included in the regression. Then, I compute the difference between reported realized gains/losses and non-discretionary RSGL as discretionary RSGL.

$$RSGL = \gamma_0 + \gamma_1 Log\_Size + \gamma_2 UNGL + \text{year fixed indicators} + \varepsilon \quad (2)$$

Where: *Log_Size* is the natural logarithm of total assets (BHCK2170); *RSGL* is realized security gains and losses (BHCK3196) divided by beginning-of-year total assets (BHCK2170); *UNGL* is cumulative unrealized gains and losses on AFS securities (BHCK1773 − BHCK1772) divided by beginning-of-year total assets (BHCK2170).

Securitization Gain Baseline Model

To test H_1, I estimate the following regression:

$$SEC\_Gain = \theta_0 + \theta_1 Post + \theta_2 Treat + \theta_3 EBPSEC + \theta_4 Post*Treat + \theta_5 EBPSEC*Post + \theta_6 EBPSEC*Treat + \theta_7 EBPSEC*Post*Treat + \Sigma\delta Control\ Variables + \varepsilon \quad (3)$$

Where: Post = 1 if an observation is in the two-year period after billion-dollar events; = 0 otherwise.

Treat = 1 if a bank holding company's headquarters is located in the affected areas; = 0 otherwise.

Control variables include discretionary LLP and realized gains or losses calculated using regressions (1) and (2) and Mkt_vol defined as idiosyncratic standard deviation of each bank's stock returns. Each bank's annual volatility is computed by regressing the monthly return in year *t*–1 on the value-weighted NYSE/AMEX index monthly returns for the same year and then taking the standard deviation of the residuals of this regression.

First, banks have greater incentives to inflate earnings when earnings before provisions and securitizations gains are lower. Therefore, I expect the estimated coefficient on EBPSEC to be significantly negative as banks inflate earnings through securitization gains. Second, EBPSEC*Post*Treat is the primary interest. The significant negative coefficient on the triple interaction term of EBPSEC*TREAT*POST would suggest that following billion-dollar events affected banks are more likely to engaging in securitization gains management, consistent with my conjecture affected banks have incentives to inflate earnings to soften the adverse impact of negative shocks on their balance sheets as the increased share of mortgages that these banks originated and securitized after natural disasters might make such manipulation less detectable. Third, the expected signs on the other types of earnings management techniques (i.e., abnormal LLP and discretionary realized gains/losses) are negative as their potential substitution effects for securitization gain management (Zhao, 2019).

To test H_2, I estimate the following regression:

$$Abnormal\ LLP = \theta_0 + \theta_1 Post + \theta_2 Treat + \theta_3 EBPSEC + \theta_4 Post*Treat + \theta_5 EBPSEC*Post + \theta_6 EBPSEC*Treat + \theta_7 EBPSEC*Post*Treat + \Sigma\delta Control\ Variables + \varepsilon \quad (4)$$

Control variables include securitization gains, discretionary realized gains and losses, LLP in the previous year, tier one capital ratio, total capital ratio, loss (an indicator), and size. First, banks have greater incentives to inflate earnings when earnings before provisions and securitizations gains are lower. Therefore, I expect the estimated coefficient on EBPSEC to be significantly negative as banks inflate earnings through abnormal LLP. Second, a significant negative (positive) coefficient on the interaction term of EBPSEC*TREAT*POST suggests that following billion-dollar events affected banks are more likely to engage in LLP management to inflate (take a bath). Third, the expected signs on the other types of earnings management techniques are negative as their potential substitution effects among earnings management techniques.

Data, Sample, and Descriptive Statistics

Natural Disaster Data

I obtain information on natural disaster events from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) from the University of South Carolina. SHELDUS contains a historical record of the names, dates, and direct losses of the natural hazards at county level from 1960 to present. I restrict the list to major natural disasters from 1998 to 2008, the period in which BHC headquarter locations are available.[1] I capture the impact on banks' earnings management of 17 major and severe natural events from 1998 to 2008, defined as disasters that last for less than 30 days and cause damage of at least at least USD 1 billion dollars, inflation adjusted based on year 2013 (Hsu et al., 2018; Barrot and Sauvagnat, 2016).[2] *[See Table 1, pg. 388]*

---

[1] I have excluded the observations where a bank holding company's headquarters is located apart from other parts of the BHC.

[2] Alabama, Florida, Geogia, and Kentucky are the four states affected by hurricanes multiple times in 2004 and 2005. Hurricanes occurring in Texas tend to provide more "new news" than hurricanes occurring in the New Orleans or South Florida basins (Ouazad and Kahn, 2022).

Descriptive Statistics

Table 2 presents the summary statistics of the main variables used in this study for affected banks and control banks for the two-year period prior to billion-dollar events and for the two-year period following such events. The affected group consists of 286 bank-year observations in the pre-period and 256 bank-year observations in the post-period. The control group consists of 1,286 bank-year observations in the pre-period and 1,169 bank-year observations in the post-period. Table 3 presents the correlation matrix among key variables. *[See Table 2, pg. 389 and Table 3, pg. 391]*

Results

Effects of Billion-Dollar Events on Securitization Gains

Table 4 presents the results of estimating securitization gain regression (3). Across all specifications, the estimated coefficient on post, -0.008, is significantly negative at the one percent level and the estimated coefficient on Post*Treat, 0.009, is significantly positive (two-tailed test). On average, securitization gains post-disasters are lower than those pre-disasters for the control banks, but securitization gains are stable for the affected banks, consistent with the evidence that increased shares and volume of mortgages affected banks originated and securitized to offload flood risk following the billion-dollar events.

Column (1) shows the results for the regression without control variables. The estimated coefficient on EBPSEC, -0.544, is significantly negative at the one percent level (two-tailed test), suggesting banks manipulate earnings through sales of securitized loans. The estimated coefficient on EPSEC*POST, 0.308, is significantly positively at the one percent level (two-tailed test). The estimated coefficient on the triple interaction term, EPSEC*POST*TREAT, -0.352, is significantly negative at the one percent level (two-tailed test), consistent with the conjecture that banks are more likely to engage in securitization gains management to increase earnings. Column (2) shows the results for the regression controlling for the two earnings management variables (discretionary LLP and discretionary realized gains and losses). The estimated coefficients on the two earnings management variables are significantly negative at the one percent level, suggesting substitution effects among three earnings management variables so as to increase earnings. The estimated coefficients on both EPSEC (-0.479) and the triple interaction term, EPSEC*POST*TREAT (-0.310) stay significantly negative at the one percent level (two-tailed test). The adjusted R^2 has increased from 0.125 to 0.292. Column (3) shows the results for the regression controlling for idiosyncratic risk. The estimated coefficients on EPSEC and the triple interaction term are like results in Column (1). The estimated coefficient on the idiosyncratic risk is insignificant. Column (4) shows the results for the full regression (3). The estimated coefficients on the two key terms are like those presented in Column (2). Together, the increased securitization gain recognition following billion-dollar natural disasters supports the conjecture that selling mortgages with worse flood risk to Fannie Mae or Freddie Mac in bunch following billion-dollar natural disasters appears to present more opportunity for affected banks to manipulate earnings through the sale of securitized loans. *[See Table 4, pg. 392]*

Effects of Billion-Dollar Events on LLP Management

Table 5 presents the results of estimating discretionary LLP regression (4). Column (1) shows the results for the regression without control variables. The estimated coefficient on EBPSEC is significantly positive at the one percent level, but the estimated coefficient on the triple interaction term, EPSEC*POST*TREAT is insignificant. Column (2) shows the results for the regression controlling for the two earnings management variables (securitization gains and discretionary realized gains and losses). The estimated coefficient on EBPSEC, -0.050, is significantly negative at the one percent level (two-tailed test). The estimated coefficients on the two earnings management variables are significantly negative at the one percent level, suggesting substitution effects among three earnings management variables to increase earnings. The estimated coefficient on the triple interaction term, EPSEC*POST*TREAT remains insignificant. The adjusted R^2 has increased from 0.027 to 0.231. Column (3) shows the results for the full regression (4). Although the adjusted R^2 has increased to 0.432, the estimated coefficient on the triple interaction term remains insignificant. Together, the insignificant results for LLP management are consistent with my argument that the affected banks' need to manage LLP to attain desired earnings management targets is limited as bunch sales of securitized loans by these banks to two main securitizing agencies offer greater opportunity following billion-dollar events. *[See Table 5, pg. 393]*

Conclusion

This study examines whether natural disasters indirectly affect earnings management channels that banks employ to increase earnings in the aftermath of multi-billion natural disasters. This study also provides evidence that affected banks appear to engage in securitization gains management without changing their behavior through loan loss estimates or strategic offerings of available-for-sale securities for realized gains or losses. These findings are consistent with my conjecture that banks are significantly more likely to increase the share of mortgages originated and securitized below the conforming loan limit to transfer climate risk to Fannie Mae and Freddie Mac, thereby indirectly masking their motivation to manage earnings through selling mortgages to the two main government sponsored agencies.

My findings document one indirect consequence of mispricing in a debt market, as Fannie Mae and Freddie Mac may bear a substantial share of the increasing climate risk. Specifically, the strategy employed by banks to manage flood risk—increasing the share of mortgages originated and securitized below the conforming loan limit—might provide these banks' more opportunities to overstate their financial strengths and thus disguise the systemic climate risk held in financial institutions' balance sheets. My findings provide insight into the types of earnings management channels to which the SEC might need to pay more attention, particularly when examining financial statements of banks that originate mortgages with high flood risk. Future research might investigate the impact of SFAS166/7 requiring consolidation of securitized loans on securitization gain management for banks originating mortgages with high flood risk.

References

Barrot, J., and J. Sauvagnat. 2016. Input specificity and the propagation of idiosyncratic shocks in production networks.*Quarterly Journal of Economics* 131 (3):1543−1592. doi: 10.1093/qje/qjw018.

Barth, M., G. Ormazabal, and D. Taylor. 2012. Asset securitizations and credit risk. *The Accounting Review* 87: 423–448.

Beatty, A., S. Chamberlain, and J. Magliolo. 1995. Managing financial reports of commercial banks: The influence of taxes, regulatory capital, and earnings. *Journal of Accounting Research* 33 (Autumn): 231–261.

Billings, M., S. Ryan, and H. Yan. 2022. Climate risk, population migration, and banks' lending and deposit-taking activities. Available at: http://dx.doi.org/10.2139/ssrn.4244372

Cavallo, E., S. Galiani, I. Noy, and J. Pantano. 2013. Catastrophic natural disasters and economic growth.*Review of Economics and Statistics* 95 (5): 1549−1561. doi: 10.1162/REST_a_00413.

Collins, J., D. Shackelford, and J. Wahlen.1995. Bank differences in the coordination of regulatory capital, earnings, and taxes. *Journal of Accounting Research* 33: 263–291.

Cortés, K. R. and P. E. Strahan. 2017. Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics* 125 (1): 182–199.

Dechow, P. M., L. Myers, and C. Shakespeare. 2010. Fair value accounting and gains from asset securitizations: A convenient earnings management tool with compensation side-benefits. *Journal of Accounting and Economics* 49: 2–25.

Flavelle, C. 2019. Bank regulators present a dire warning of financial risks from climate change. *New York Times.* https://www.nytimes.com/2019/10/17/climate/federal-reserve-climate-financial-risk.html

Hsu, P., H. Lee, S. Peng, and L. Yi. 2018. Natural disasters, technology diversity, and operating performance. *The Review of Economics and Statistics* 100 (4): 619–630. http://dx.doi.org/10.1162/rest_a_00738

Maso, D. L., K. Kanagaretnam, G. J. Lobo, and F. Mazzi. 2022. Does disaster risk relate to banks' loan loss provisions? *European Accounting Review* 33 (3): 825–854. https://doi.org/10.1080/09638180.2022.2120513

Meisenzahl R. 2023. How climate change shapes bank lending: Evidence from portfolio reallocation. Working paper. https://doi.org/10.21033/wp-2023-12

Ouazad, A. and M. Kahn. 2022. Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disaster. *The Review of Financial Studies* 35 (8): 3617–3665.

Sastry, P. 2022. Who bears flood risk? Evidence from mortgage markets in Florida. Working Paper.

Wu, K., H. Zhang, S. Wang, Y. Qiu, and M. S. Seasholes. 2022. How do natural disasters impede corporate earnings management? Available at: http://dx.doi.org/10.2139/ssrn.3676848

Yang Q., and G. Bai. 2024. The effect of natural disasters on big bath earnings management of banks: evidence from the 2005 US hurricane season. *Accounting and Business Research* 54:673−699.DOI: 10.1080/00014788.2023.2258781

Zhao, Q. 2019. Interaction of securitization gains and loan loss provisions: Fair value accounting and credit risk retention. *Journal of Business, Finance and Accounting* 46 (7–8): 813−842.https://doi.org/10.1111/jbfa.12381

Appendix: Variable Definitions (Alphabetical order)

Codes in BHC Y9-C reports are reported in parentheses

BEGLLA = the lagged annual loan loss allowance (BHCKB522) divided by beginning-of-year total loans (BHCK2122)

BEGNPL = lagged nonperforming assets (BHCK5525 + BHCK5526) divided by beginning-of-year total loans (BHCK2122)

BM: natural log of book-to-market ratio

abnormal_LLP: discretionary LLP estimated from regression (1)

discr_RSGL: discretionary realized gains/losses from AFS securities estimated from regression (2)

Derivatives: total notional amount of derivatives [sum (BHCKA126, BHCKA127, BHCK8723, BHCK8724, BHCK8725, BHCK8726, BHCK8727, BHCK8728)] scaled by the beginning of total assets (BHCK2170)]

EBPSEC: income before taxes, extraordinary items, loan loss provisions, and securitization income in year t (BHCK4301 + BHCK4230 − BHCKB493) scaled by the beginning of total assets (BHCK2170)]

EBSEC: income before taxes, extraordinary items, and securitization income in year t (BHCK4301 − BHCKB493) scaled by the beginning of total assets (BHCK2170)]

Lag_tier 1: tier one risk based capital ratio (bhck8274/lagBHCKA223) at the end of year t-1

Lag_TCAP: total risk-based capital ratio (bhck3792/BHCKA223) at the end of year t-1

LLP = the annual loan loss provision (BHCK4230) divided by beginning-of-year total loans (BHCK2122)

Log_Size = the natural logarithm of total assets (BHCK2170)

Loss = 1 if earnings (BHCK4340) are less than zero; otherwise, = 0

Mkt_vol: idiosyncratic standard deviation of each bank's stock returns; each bank's annual volatility is computed by regressing the monthly return in year t-1 on the value-weighted NYSE/AMEX index monthly returns for the same year with the standard deviation of the residuals of this regression (Dechow et al., 2010)

Past LLP: loan loss provision (BHCK4230) at year t-1

Post = 1 if an observation is in the two-year period after billion-dollar events; = 0 otherwise

RSGL = realized security gains and losses (BHCK3196) divided by beginning-of-year total assets (BHCK2170)

sec_gain: securitization income at the end of year t (BHCKB493) scaled by the beginning of total assets (BHCK2170)]. I assume that all securitization gains are discretionary, following Dechow et al. (2010).

Treat = 1 if a bank holding company's headquarters is located in the affected areas; = 0 otherwise

UNGL = cumulative unrealized gains and losses on AFS securities (BHCK1773 − BHCK1772) divided by beginning-of-year total assets (BHCK2170)

Table 1: List of Major Disasters

Abbreviations for U.S. states used in the table: AL (Alabama), AK (Alaska), AZ (Arizona), AR (Arkansas), CA (California), CO (Colorado), CT Connecticut), DE (Delaware), FL (Florida), GA (Georgia), HI (Hawaii), ID (Idaho), IL (Illinois), IN (Indiana), IA (Iowa), KS (Kansas), KY (Kentucky), LA (Louisiana), ME (Maine), MD (Maryland), MA (Massachusetts), MI (Michigan), MN (Minnesota), MS (Mississippi), MO (Missouri), MT (Montana), NE (Nebraska), NV (Nevada), NH (New Hampshire), NJ (New Jersey), NM (New Mexico), NY (New York), NC (North Carolina), ND (North Dakota), OH (Ohio), OK (Oklahoma), OR (Oregon), PA (Pennsylvania), RI (Rhode Island), SC (South Carolina), SD (South Dakota), TN (Tennessee), TX (Texas), UT (Utah), VT (Vermont), VA (Virginia), WA (Washington), WV (West Virginia), WI (Wisconsin), and WY (Wyoming).

Disaster	Year	Month	Type	Affected States
Bonnie	1998	8	Hurricane	NC, VA
Georges	1998	9	Hurricane	AL, FL, LA, MS
Floyd	1999	9	Hurricane	CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT
Alison	2001	6	Hurricane	AL, FL, GA, LA, MS, PA, TX
Isabel	2003	9	Hurricane	DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV
Southern California Wildfires	2003	10	Hurricane	CA
Charley	2004	8	Hurricane	FL, GA, NC, SC
Jeanne	2004	9	Hurricane	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Ivan	2004	9	Hurricane	AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV
Frances	2004	9	Hurricane	AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV
Dennis	2005	7	Hurricane	AL, FL, GA, MS, NC
Katrina	2005	8	Hurricane	AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN
Rita	2005	9	Hurricane	AL, AR, FL, LA, MS
Wilma	2005	10	Hurricane	FL
Midwest Floods	2008	6	Floods	IA, IL, IN, MN, MO, NE, WI
Gustav	2008	9	Hurricane	AL, AR, LA, MS
Ike	2008	9	Hurricane	AR, IL, IN, KY, LA, MI, MO, MS, OH, PA, TN, TX

Table 2: Summary Statistics

	post	N Obs	Variable	N	Minimum	Mean	Median	Maximum	Std Dev
Control group	0	1268	sec_gain	1268	0.000	0.003	0.000	0.119	0.013
			abnormal_LLP	1268	-0.040	-0.001	0.000	0.027	0.007
			discr_RSGL	1268	-0.004	0.000	0.000	0.005	0.001
			EBPSEC	1268	-0.015	0.022	0.022	0.044	0.009
			lag_Mkt_Vol	1268	0.024	0.081	0.079	0.300	0.033
			derivative	1268	0.000	2.363	0.137	56.995	7.578
			loss	1268	0.000	0.011	0.000	1.000	0.105
			pastLLP	1263	-0.002	0.007	0.005	0.054	0.008
			lag_tier1	1268	0.068	0.113	0.096	0.991	0.087
			lag_TCAP	1268	0.085	0.132	0.122	0.367	0.036
			log_size	1268	12.244	16.542	16.838	19.009	1.888
	1	1169	sec_gain	1169	0.000	0.002	0.000	0.119	0.009
			abnormal_LLP	1169	-0.040	-0.001	0.000	0.027	0.007
			discr_RSGL	1169	-0.005	0.000	0.000	0.005	0.001
			EBPSEC	1169	-0.015	0.020	0.020	0.044	0.010
			lag_Mkt_Vol	1169	0.024	0.071	0.062	0.475	0.041
			derivative	1169	0.000	2.868	0.125	56.995	8.391
			loss	1169	0.000	0.072	0.000	1.000	0.258
			pastLLP	1162	-0.003	0.009	0.005	0.077	0.012
			lag_tier1	1169	0.049	0.125	0.102	0.997	0.123
			lag_TCAP	1169	0.079	0.137	0.124	0.367	0.043
			log_size	1169	12.244	16.729	16.897	19.009	1.876
Affected group	0	286	sec_gain	286	0.000	0.002	0.000	0.119	0.012
			abnormal_LLP	286	-0.040	-0.001	0.000	0.010	0.006
			discr_RSGL	286	-0.002	0.000	0.000	0.003	0.001
			EBPSEC	286	-0.015	0.021	0.022	0.042	0.008
			lag_Mkt_Vol	286	0.040	0.087	0.085	0.269	0.026
			derivative	286	0.000	2.647	0.138	48.561	7.424
			loss	286	0.000	0.010	0.000	1.000	0.102
			pastLLP	282	-0.001	0.007	0.006	0.054	0.007

		lag_tier1	286	0.070	0.100	0.093	0.188	0.024
		lag_TCAP	286	0.087	0.126	0.120	0.201	0.019
		log_size	286	12.244	16.435	16.945	19.009	2.013
1	256	sec_gain	256	0.000	0.002	0.000	0.119	0.011
		abnormal_LLP	256	-0.040	-0.001	0.000	0.013	0.005
		discr_RSGL	256	-0.004	0.000	0.000	0.003	0.001
		EBPSEC	256	-0.015	0.021	0.020	0.044	0.008
		lag_Mkt_Vol	256	0.024	0.060	0.051	0.163	0.024
		derivative	256	0.000	3.590	0.214	56.995	8.643
		loss	256	0.000	0.027	0.000	1.000	0.163
		pastLLP	255	-0.003	0.006	0.004	0.048	0.007
		lag_tier1	256	0.070	0.102	0.091	0.218	0.028
		lag_TCAP	256	0.101	0.129	0.121	0.254	0.026
		log_size	256	12.244	16.958	17.443	19.009	1.889

Note: Table 2 presents summary statistics for key variables in the sample period 1998−2008.

Table 3: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
sec gain (1)	1	-0.452	-0.022	-0.015	-0.027	-0.327	0.007	0.012	-0.035	0.447	0.050	0.175	0.150
		<.0001	0.236	0.428	0.142	<.0001	0.686	0.525	0.059	<.0001	0.007	<.0001	<.0001
abnormal_LLP(2)	-0.307	1	-0.020	0.013	-0.128	0.156	-0.049	-0.137	-0.236	-0.590	-0.124	-0.172	-0.209
	<.0001		0.272	0.483	<.0001	<.0001	0.008	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
post (3)	-0.012	-0.008	1	-0.006	-0.088	-0.094	-0.189	0.036	0.141	0.034	0.053	0.065	0.065
	0.519	0.653		0.756	<.0001	<.0001	<.0001	0.047	<.0001	0.063	0.004	0.000	0.000
treat (4)	-0.002	0.007	-0.006	1	0.016	-0.008	-0.022	0.024	-0.045	-0.053	-0.072	-0.070	0.010
	0.902	0.683	0.756		0.379	0.666	0.235	0.199	0.014	0.004	<.0001	0.000	0.580
discr_RSGL (5)	0.056	-0.075	-0.034	0.026	1	0.158	0.114	0.144	-0.006	0.157	0.240	0.226	-0.058
	0.002	<.0001	0.063	0.149		<.0001	<.0001	<.0001	0.742	<.0001	<.0001	<.0001	0.001
EBPSEC (6)	0.021	0.076	-0.103	-0.001	0.036	1	-0.007	-0.067	-0.326	-0.127	0.210	0.125	0.206
	0.251	<.0001	<.0001	0.960	0.051		0.722	0.000	<.0001	<.0001	<.0001	<.0001	<.0001
lag_Mkt_Vol (7)	-0.071	-0.039	-0.293	-0.002	0.039	0.040	1	-0.052	0.236	0.338	-0.048	-0.030	-0.195
	<.0001	0.031	<.0001	0.912	0.034	0.029		0.005	<.0001	<.0001	0.009	0.104	<.0001
derivative (8)	0.530	-0.263	0.041	0.029	-0.029	0.197	-0.065	1	-0.023	0.160	-0.097	-0.093	0.385
	<.0001	<.0001	0.026	0.117	0.110	<.0001	0.000		0.204	<.0001	<.0001	<.0001	<.0001
loss (9)	-0.048	-0.168	0.141	-0.045	0.022	-0.244	0.154	-0.009	1	0.309	-0.022	-0.007	-0.042
	0.009	<.0001	<.0001	0.014	0.221	<.0001	<.0001	0.605		<.0001	0.232	0.684	0.023
pastLLP (10)	0.244	-0.527	-0.081	-0.011	0.123	0.038	0.342	0.281	0.183	1	0.069	0.159	0.211
	<.0001	<.0001	<.0001	0.567	<.0001	0.037	<.0001	<.0001	<.0001		0.000	<.0001	<.0001
lag_tier1 (11)	-0.338	0.110	0.075	-0.079	0.035	-0.240	0.032	-0.539	0.036	-0.157	1	0.894	-0.164
	<.0001	<.0001	<.0001	<.0001	0.057	<.0001	0.083	<.0001	0.051	<.0001		<.0001	<.0001
lag_TCAP (12)	-0.146	0.074	0.067	-0.056	0.077	-0.101	-0.010	-0.192	0.031	-0.049	0.785	1	-0.147
	<.0001	<.0001	0.000	0.002	<.0001	<.0001	0.586	<.0001	0.090	0.008	<.0001		<.0001
log_size (13)	0.507	-0.244	0.066	0.018	-0.043	0.242	-0.145	0.847	-0.047	0.241	-0.534	-0.187	1
	<.0001	<.0001	0.000	0.339	0.020	<.0001	<.0001	<.0001	0.011	<.0001	<.0001	<.0001	

Note: Table 3 presents the Pearson (above the diagonal) and Spearman (below the diagonal) correlations for key variables in the sample period 1998−2008.

Table 4: Results of Estimating the Association Between Natural Disasters and Securitization Gains

Variable	Pred. sign	SEC_GAIN (1)	SEC_GAIN (2)	SEC_GAIN (3)	SEC_GAIN (4)
Intercept	?	0.015***	0.013***	0.014***	0.013***
post	?	-0.008***	-0.009***	-0.008***	-0.009***
treat	?	-0.001	-0.002	-0.001	-0.002
EBPSEC	–	-0.544***	-0.479***	-0.545***	-0.479***
Post*Treat	?	0.009***	0.008***	0.009***	0.008***
EBPSEC*post	?	0.308***	0.331***	0.312***	0.330***
EBPSEC*treat	?	0.003	0.066	0.004	0.066
EBPSEC*Treat*Post	–	-0.352***	-0.310***	-0.354***	-0.310***
abnormal_LLP	–		-0.740***		-0.740***
discr_RSGL	–		-0.572***		-0.568***
lag_Mkt_Vol	?			0.004***	-0.001***
Adj R2		0.125	0.292	0.125	0.292

Note: Two-tailed test; *** significant at the one percent level; ** significant at the five percent level; * significant at the ten percent level.

Table 5: Results of Estimating the Association Between Natural Disasters and Abnormal LLP

Variable	Pred. sign	Abnormal_LLP (1)	Abnormal_LLP (2)	Abnormal_LLP (3)
Intercept	?	-0.003***	0.001**	0.007***
post	?	-0.001	-0.003***	0.000
treat	?	-0.002*	-0.002*	-0.002*
EBPSEC	–	0.075***	-0.050***	0.004
Post*Treat	?	-0.001	0.001	-0.001
EBPSEC*post	?	0.026	0.111***	0.018
EBPSEC*treat	?	0.105**	0.081*	0.077**
EBPSEC*Treat*Post	?	0.044	-0.030	0.010
sec_gain	–		-0.258***	-0.148***
discr_RSGL	–		-0.977***	-0.381***
derivative	–			0.000**
loss	?			-0.005***
pastLLP	?			-0.263***
lag_tier1	?			-0.012***
lag_TCAP	?			0.015***
log_size	?			0.000***
Adj R2		0.027	0.231	0.432

Note: Two-tailed test; *** significant at the one percent level; ** significant at the five percent level; * significant at the ten percent level.