Strategic Portfolio Management: Evidence from a Natural Experiment*

MICHAEL YUBO LIU†

July 2018

Abstract

This paper examines strategic portfolio management by studying portfolio decisions and transactions of U.S. insurers. Using Hurricane Katrina as an exogenous shock, I find evidence that supports strategic portfolio management for insurers. Anticipating bond fire sales by affected insurers, unaffected insurers build up cash holdings by selling bonds before Hurricane Katrina, and purchase back the same bonds from affected insurers at fire sale prices after Hurricane Katrina. On average, unaffected insurers earn α of about 0.70 bps per week for their bond portfolios. Stocks of public unaffected insurers also earn α of about 70 bps per month. This is consistent with models in which unconstrained investors take advantage of the price pressure from constrained investors. These results highlight the strategic portfolio management motive for an important institutional investor in the U.S. bond market.

JEL Classifications: G11, G14, G22, G23

Key words: Strategic Portfolio Management; Natural Experiment; Fire Sales

---

*I am greatly indebted to Neal Galpin, Joachim Inkmann, Hae Won Jung, and Jordan Neyland for their extensive help and support. I thank NAIC for providing data. I thank Lynnette Purda (discussant), Martin Boyer, Jason Smith, Yoko Shirasu (discussant), Richard Lowery, Jonathan Berk, In Jung Song (discussant), Pedro Barroso (discussant), Thomas Ruf, Buhui Qiu, Spencer Martin, Bruce Grundy, Vincent Gregoire, Sturla Fjesme, Garry Twite, Alberto Manconi (discussant), Hayong Yun, Ran Duchin, Hendrik Bessembinder, David Dicks, Abhiroop Mukherjee, Hendrick (Henk) Berkman as well as the conference participants at the University of Melbourne Brown Bag, 2013 Research Reference Groups of Australia Centre for Financial Studies, 2014 Ottawa Northern Finance Association (NFA), 2015 Chicago Midwest Finance Association (MFA), 2015 Orlando Financial Management Association (FMA) Annual Meeting, 2015 Orlando FMA Doctoral Consortium, 2015 Financial Reserach Association Annual Conference (FIRN), 2016 Arizona State University Sonoran Winter Finance Conference, and University of Auckland

†Assistant Professor of Finance, Department of Finance, School of Economics and Wang Yanan Institute of Studies in Economics, Xiamen University, China. Email: lyb1231@xmu.edu.cn.

1 Introduction

Since Keynes (1936), finance research has well shown that financial institutions may hold cash and other liquid assets as a precaution against subsequent liquidity shocks.[1] A less well-understood incentive for holding cash is to take advantage of the shocks by acquiring assets at discounted prices in financial markets.[2] However, to date, there is little research that documents evidence of such strategic incentives in portfolio management. This paper fills this gap by empirically examining the strategic consideration in the asset portfolio management of insurance companies. Using Hurricane Katrina as an exogenous liquidity shock, I find that anticipating bond fire sales by affected insurers, unaffected insurers sell bonds to build up their cash holdings before and purchase back the same bonds at fire sales prices from affected insurers after Hurricane Katrina.

The following simple example places Diamond and Rajan (2011) model (DR hereafter) in the context of insurers to demonstrate the manner in which insurers engage in strategic portfolio management. Similar to the "banks" in DR, public general insurance companies enjoy limited liability and hold long-term assets (e.g. corporate bonds and municipal bonds) financed with short-term liability (e.g. policyholders' claims). Insurance firms and their portfolio managers have strong incentives to maximize portfolio returns.[3] An insurance firm may become insolvent or bankrupt if the firm is unable to pay their policyholders' claims within a certain time period. Now, consider a coastal insurer (e.g. a Florida insurer) as the illiquid financial institution that face future liquidity shocks in DR, and consider an inland insurer (e.g. a Utah insurer) as the liquid financial institution that does not face the liquidity shocks. As the probability of the liquidity shock (e.g. Hurricane Katrina) and the

[1]See Froot, Scharfstein, and Stein (1993); Acharya, Almeida, and Campello (2007); Acharya, Shin, and Yorulmazer (2011); Ashcraft, McAndrews, and Skeie (2011); Cornett, McNutt, Strahan, and Tehranian (2011); Acharya and Skeie (2011); Diamond and Rajan (2011); Acharya and Merrouche (2012).

[2]For example, Acharya, Shin, and Yorulmazer (2011) has shown that banks' ex-ante choice of liquidity can be driven by a strategic consideration, e.g. to acquire assets cheap at fire sale prices during financial crises. In Diamond and Rajan (2011), they also showed that anticipating a potential fire sale, liquid financial institutions expect high returns, reducing their incentives to provide liquidity.

[3]Insurance firms have incentives to maximize the yield on their investments because investment portfolio return is one of the primary sources of earnings for insurers (Becker and Ivashina, 2015). Portfolio managers of insurers (whether in-house or outsourced) also have incentives to maximize the investment yield because of their compensation structure. According to NAIC (2011), annual investment-management fees for core fixed-income mandates are generally in the range of 10 to 25 basis points (bps) of assets under management. Performance of portfolio managers is evaluated against a standard market metric or a custom index designed to meet the insurers investment objectives (NAIC, 2011)

expected liquidity demand increase, long-term assets are expected to sell at fire sale prices in future, and the return on holding cash today to buy assets cheaply in future is higher, implying less liquidity provision through trading before the shock. In other words, both Florida and Utah insurers will hold or build up cash holdings before the shock. Because of the exogeniety of a hurricane event[4], the cash holdings may not be enough for some coastal insurers and they thus have to liquidate illiquid assets quickly at fire sale prices after the shocks. Utah insurers that built up cash holdings before the hurricane are able to take advantage of the discounted prices and earn abnormal returns.

Using a sample of U.S. insurers from 2002 through 2008, I find evidence that is consistent with strategic portfolio management in insurers' asset portfolios. First, I find that in a two-quarter period before Hurricane Katrina, both "affected" and "unaffected" insurers significantly increase their cash holdings by selling bonds. This is consistent with the DR's prediction that liquidity provision is rare before a shock if assets are expected to only transacted at fire sale prices in future. I define affected insurers as insurers that witness rating downgrades or negative watch by rating agencies immediately after Hurricane Katrina, and that also conduct hurricane-related insurance lines of business (e.g. homeowner insurance, commercial insurance, fire, reinsurance property) in the states of Louisiana, Mississippi, and Alabama.[5]

Difference-in-differences analysis shows that, relative to affected insurers, unaffected insurers significantly decreases cash holdings by an additional -6.22% after Hurricane Katrina, while they significantly increases bond holdings by an additional 6.33%. This indicates that unaffected insurers use cash to purchase bonds after Hurricane Katrina. Interestingly, the 6.22% change in cash holdings post-Katrina is roughly equal to the differences in cash holdings bewteen unaffected and affected insurers before Hurricane Katrina. For example, the pre-Katrina cash holdings are about 15% and 9% for unaffected and affected insurers, respectively. To link the post-Katrina portfolio decisions with pre-Katrina cash holdings,

[4]By exogeniety, I mean that before a hurricane strike no insurer has perfect information about the total costs of the hurricane and the exact areas that the hurricane will affect.

[5]I also use an alternative definition of affected/unaffected by following Massa and Zhang (2017). They use Holborn Report which lists the names of general (re)insurance companies along with their 2004 market shares in the states of Louisiana, Mississippi, and Alabama, and whether they have rating or outlook changes immediately after the hurricane. Since Holborn's methodology is similar to mine, the identified affected/unaffected insurers also very similar, so are the results

I sort sample insurers into quartiles according to pre-Katrina raw(and abnormal) cash holdings. As expected, the difference-in-differences effect concentrates only on insurers in top quartile cash group. Several placebo tests show that the effect is not significant if we change the event time.[6]

Transaction-level evidence lends further support to the strategic portfolio management hypothesis. To identify the bonds that are most likely to be purchased by unaffected insurers after Hurricane Katrina, I estimate a probit model where the dependent variable equals one if insurers buy a bond during a two-quarter period after Hurricane Katrina, and zero otherwise. Controlling for bond and insurer characteristics, I find that, relative to affected insurers, unaffected insurers with higher pre-Katrina cash holdings are more likely to purchase bonds after Hurricane Katrina. In addition, larger insurers, insurers with lower non-invested assset holdings, lower leverage, lower operating cash flow variance are more likely to purchase bonds after Hurricane Katrina. Insurers prefer younger bonds, bonds with larger issue size and better credit rating. To further understand insurers' decision to purchase bonds, I estimate the probit model for several sub-samples. For example, in one sub-sample I focus on the same bonds sold before Katrina by unaffected insurers and purchased back by the same unaffected insurers after Hurricane Katrina from affected insurers. Results suggest that the sub-sample exhibits the strongest results, suggesting that it is those bonds we identify in the sub-sample drive the insurer's portfolio decision.

In theory, it is the perspective of buying bonds cheaply at fire sale prices that attracts unaffected insurers to accumulate cash pre-Katrina. To test fire sales, I first assign bonds into quartiles according to estimated probability of buying after Hurricane Katrina. Using a simple mean-adjusted model, I estimate median cumulative abnormal returns (MCAR) for bonds with top quartile and bottom quartile buying probability. Results suggest significant ngative MCAR for a [-45,+45] event-week period for top quartile buying probability group, but insignificant results for bottom quartile group. The MCAR is as large as about -11% for the [-45,0] event-week period. Further analysis suggests that the effect concentrates on bonds that are sold by affected insurers, suggesting that indeed unaffected insurers

[6] While 2004Q3 is marginally significant, we confirm that it is due to extreme hurricane activities within a month period for that quarter.

buy bonds sold by affected insurers at fire sale prices. Overall, I show that there are bond fire sales, and these fire sales only concentrate on bonds that are sold pre-Katrina and purchased back post-Katrina by unaffected insurers from affected insurers. Another important investment in the asset portfolios of insurers is stock investment. I repeat the transaction-level analysis for stocks, but do not find significant results. One explanation is that insurance sector as a whole hold a very small portion of the stock market. It is very unlikely for such small player in the market to generate meaningful price pressure to affect prices. Confirm the conjecture, the MCAR tests show no sign of significant price discount for stocks.

The story of strategic portfolio management is not complete without an examination of thee performance of insurers. I examine both the insurer's investment portfolio performance and, for a sub-sample of publicly listed insurers, the insurers' stock price performance. Results suggest insurers earn significant positive abnormal returns, supporting strategic portfolio management hypothesis. Specifically, I show that bonds traded by insurers, especially those bonds net purchased by unaffected insurers, earn α of about 0.59 to 0.83 bps per week. Insurers also earn α for their shareholders. Controlling for Carhart (1997) four-factors and the Pástor and Stambaugh (2003) liquidity factors, unaffected insurers' stocks earn signficant α of about 60 to 80 bps per month.

The bond market provides an ideal laboratory in which to investigate the strategic motive in trading and portfolio management because the major bond investors are insurance firms. Insurance firms have liquidity needs that arise from an observable event (e.g. a hurricane).[7] Moreover, while the timing of a natural disaster is relatively predictable, there is important variability in the magnitude of the effect and the exact firms affected by the disaster. In addition, compared with the traditional candidates in research of portfolio management (e.g. banks and open-end funds), insurance firms suffer less from performance-based endogenous liquidity needs.[8] The only major liquidity demands stem

[7]Policyholders are eligible to claim when insured properties are damaged or destroyed. Local residents may receive monetary support from the United States Federal Emergency Management Association, and insured residents supplement these funds by claiming to their insurance firms.

[8] Performance-based endogenous liquidity needs are very unlikely for insurers because insurers face long-term end investors and are equipped with long lock-ups and penalties for early withdrawals (Manconi, Massa, and Yasuda, 2012).

from policyholders' claims. To the extent that identifying determinants of portfolio liquidity requires exogenous variations in liquidity demands, insurers provide the best chance to understand clearly the portfolio-liquidity decisions.

There are some alternative explanations for and concerns about my observation. First, if the strategic motive story works, other investors that are not affected by Hurricane Katrina should also be able to exploit the fire sale discounts. One immediate investor is life insurer. I thus repeat the holding-level and transaction-level tests for life insurers and find results that are very similar to my sample of general insurers. Public life insurers on average earn α of 165 bps for their shareholders per month during my sample period. Second, the assignment of treatments and controls is not purely random in my difference-in-differences tests, and might be correlated with insurers' characteristics (e.g. indeed, insurers may well self-select themselves into disaster states). To address this issue, I match insurers before Hurricane Katrina along several dimensions and find similar results. I also examine the parallel trend assumption and results suggest insignificant difference in trends between affected and unaffected insurers before Hurricane Katrina. Finally, to futher rule out the liquidity provision story, I focus on a sub-sample where the affected and unaffected insurers belong to the same insurance group. I use this sample because, if liquidity provision is prevailing, I should expect to witness the strongest effect in the sample where unaffected and affected insurers belong to the same insurance group. Results suggest otherwise, lending further support to the strategic portfolio management hypothesis.

This paper builds on and contributes to several strands of literature. First, it contributes to the literature on portfolio management of institutions by providing empirical evidence for the strategic motive in management portfolios. Despite the well-documented evidence of precautionary liquidity hoarding by banks (e.g. Ashcraft, McAndrews, and Skeie (2011); Acharya and Merrouche (2012)), recent studies by Diamond and Rajan (2011) and Acharya, Shin, and Yorulmazer (2011) note the theoretical possibility of strategic liquidity management. However, given the unavailability of proprietary transaction data, no empirical evidence has been produced, though anecdotal evidence seems to be consistent with the argument for the existence of strategic liquidity management. As noted by Acharya, Shin, and Yorulmazer (2011) in their concluding remarks, " It remains an important empirical question to differentiate and measure the importance of strategic motive relative to the more traditional precautionary motive for holding liquidity."

This paper also contributes to a growing strand of literature on portfolio choices of insurance firms. Financial economists are interested in insurers partially because they play an important role in transmitting funds to provide credit to industrial firms in real economy.[9] However, the existing literature overwhelmingly argues that capital regulations drive the insurers' asset-side behavior (e.g. Ellul, Jotikasthira, and Lundblad (2011); Merrill, Nadauld, Stulz, and Sherlund (2012); Koijen and Yogo (2016, 2015)). This paper demonstrates that even in a highly regulated industry such as the insurance industry, not all portfolio decisions are driven by regulations. The most similar research to this paper is Becker and Ivashina (2015), who demonstrate that by holding regulatory constraints constant, insurers exhibit a significant propensity to buy riskier assets to achieve higher yields. For the sample period from 2004Q1 through 2010Q3, they conclude that the higher yields reflect market risk rather than superior bond picking or better access to underpriced bonds. However, unlike Becker and Ivashina (2015), this paper shows that, by strategically selling and buying back the same bonds around a liquidity event, insurers are able to earn *alpha* by creating better access to underpriced bonds than other investors in the financial markets.

This paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and statistics. Section 4 presents the empirical results. Section 5 performs various robustness tests, and Section 6 concludes.

2 Relevant Literature

Given the economic significance of insurers in U.S. debt markets, it is not surprising to see a large growing body of literature dedicated to understanding the trading behavior of insurers. Since U.S. insurance sector is highly regulated, most existing studies focus on the

[9]According to the U.S. Flow of Funds Accounts, the insurance sector held \$2.3 trillion in bonds in 2010more than the bond holdings of mutual and pension funds taken together (Becker and Ivashina, 2015). They also had \$4,965 billion policyholders' liabilities in 2012, which is substantial even when compared with \$6,979 billion in savings deposits at U.S. depository institutions (Koijen and Yogo, 2016).

roles played by regulations in portfolio decisions of insurers (see Ellul, Jotikasthira, and Lundblad (2011); Manconi, Massa, and Yasuda (2012); Ellul, Jotikasthira, Lundblad, and Wang (2012); Merrill, Nadauld, Stulz, and Sherlund (2012, 2013); Becker and Opp (2013)). Research evidence cannot yet conclude that all the asset-side behavior of insurers is driven by regulations.

Only until recently, one study has started to consider other incentives driving insurers' portfolio decision. Becker and Ivashina (2015) demonstrate that by conditioning on non-binding capital requirements, insurance portfolios, compared to those of pension funds and mutual funds, are systematically biased towards riskier asset classes with higher yield. The "reaching for yield" incentive is consistent with profit maximizing insurers as they maximize their investment returns given regulatory constraints on capital requirements. Other incentives or behavior, e.g. strategic motive, may also play an role in portfolio decisions if insurers are maximizing their investment returns. This paper follows and contributes to this strand of literature and try to answer the following questions, namely, does strategic motive plays an role in portfolio decisions and trading of insurers?

In a complete frictionless market, there is no incentive for insurers to manage liquidity and hold low-yield liquid assets to smooth their claim payouts. If markets are perfectly liquid, insurers can smooth claims by using normal operating cash flows or capital markets at no cost. If markets are complete, insurers are able to establish contingent contracts for the provision of cash ex-ante for every possible state in the future. However, insurance markets and capital markets are far from complete and frictionless. Despite capital markets (e.g. catastrophe bonds) and residual market mechanisms (e.g. reinsurers, state guaranty funds), disaster risk is considered "uninsurable", implying that it is extreme expensive and impossible for insurers to write contingent contracts ex-ante against every future disaster.

In addition, given the various frictions present in the market, external financing also becomes very expensive or unavailable at the precise time it is most needed. Overwhelming evidence from literature demonstrates that market frictions cause insurers' capital to adjust very slowly after disaster shocks. Charging a higher insurance premium after disasters is also very difficult. As noted by Darrell Duffie in his 2010 presidential address, in the absence of other capital shocks, extremely slow capital movements lead to slow insurance-premium adjustments (Duffie, 2010).

Finally, the law of large numbers – the fundamental mechanism of insurance – does not work in the case of extreme disaster events. It is extremely difficult, if not impossible, for insurers to predict disaster claims. Large disaster claims can suddenly wipe out the liquidity pool of the entire insurance sector, not to mention any single exposed insurer.[10]

If market incompleteness and market frictions induce inter-temporal liquidity considerations for insurers to hold cash, do such incentives differ among insurers? The literature generally suggests there are two motives for holding cash, namely, a precautionary motive and a strategic motive. The tension between the two motives is the probability of a liquidity shock and the expected aggregate liquidity. According to Acharya, Shin, and Yorulmazer (2011) and Gale and Yorulmazer (2013), the precautionary motive is an increasing function of the probability of liquidity shock. Given frictions and market incompleteness (e.g. expensive external financing, expensive bankruptcy, aggregate illiquidity), insurers that expect a high probability of liquidity shock will hold cash to insure against future uncertain liquidity requirements. For insurers that do not expect to receive a future liquidity shock, the decision about whether to hold cash depends on the expected aggregate liquidity, or in other words, the expected deviation of prices from fundamentals. The endogenous choice of insurers' liquidity is then a declining function of aggregate liquidity. If the expected aggregate liquidity is low, the deviation of prices from fundamentals is high, creating a motive to hold cash to exploit discounted prices. Conversely, if aggregate liquidity is expected to be high, the expected gains from exploiting are low, leading insurers to carry low liquid buffers.

According to Diamond and Rajan (2011) and other related research, one must demonstrate strategic portfolio management in two stages. In the first stage, both unaffected insurers (i.e. the strategic insurers) and affected insurers build up cash holding. They may do so by liquidating part of their stock and bond holdings. In the second stage, exogenous liquidity shock materializes and affected insurers may need additional cash by unwinding

[10] Anecdotally, the 2012 10-K file of the insurance company ACE Group Ltd. discloses on page 89, "Despite our safeguards, if paid losses accelerated beyond our ability to fund such paid losses from current operating cash flows, . . . we could be required to liquidate a portion of our investments, potentially at distressed prices."

additional bond or stock holdings. Unaffected insurers may earn profits by providing liquidity. The tension between liquidity provision and strategic trading lies critically on the bonds or stocks they traded. A strategic insurers should sell in the first stage, buy back the same bond or stock in the second stage at discounted price and earn abnormal profits. Indeed, Diamond and Rajan (2011) demonstrate that the gains from acquiring impaired institutions at fire-sale prices make it attractive for liquid institutions to hoard liquidity. Similarly, Acharya, Shin, and Yorulmazer (2011) and Acharya, Gromb, and Yorulmazer (2012) demonstrate that limited pledgeability of risky cash flows, coupled with the potential for future acquisitions at fire-sale prices, induces banks to hoard liquidity in their portfolios.

More formally, I can recast the Diamond and Rajan (2011) model in an insurer setting. First, it can be assumed that no insurers have perfect information about the actual cost of a disaster, though insurers know a disaster is likely. Before the disaster (t=-1), insurers estimate their disaster claims though the estimation is imperfect. Those that expect large claims from the disaster build up cash holding by selling bonds. Anticipating fire sales in the bond markets, others that do not expect claims may also build up cash holdings because the gains from acquiring bonds at discount prices outweigh the costs of holding cash. Given the exogenous liquidity shock, affected insurers may be forced to sell additional bonds at fire sale prices. A strategic insurer should exploit this opportunity by selling and buying back the same bond at discounted price.[11] Exploiting Hurricane Katrina in a natural experiment, this paper differs from past research in that it explores individual transaction data to examine the importance of strategic motive in portfolio decision, and at the same time, it assesses the empirical relevance of Diamond and Rajan (2011) theory.

[11] Past and recent crises have witnessed several occasions in which such predatory trading has occurred. For example, predatory behavior against Long-term Capital Management in 1998 (Cai, 2009); predatory behavior against several hedge funds during the 2008 Global Financial Crisis is documented in *Financial Times*; and the memorable account of how the National City Bank, which eventually became Citibank, grew from a small treasury unit into one of the biggest commercial banks by strategically building up liquidity and benefit from the difficulties of its competitors in the middle of crises: see Acharya, Shin, and Yorulmazer (2011) and Cleveland and Huertas (1985) for details.

3 Data

This section describes the sample compiling process, sample statistics, variable constructions, and provides descriptive statistics.

3.1 Sample Construction

I compile the data for the analysis from multiple sources for the 2001:Q1 to 2008:Q4 period. National Association of Insurance Commissioners (NAIC) provides insurance firms' holding and transaction data. I complement NAIC data with the Mergent Fixed Income Securities Database (FISD) and Trade Reporting and Compliance Engine (TRACE). I also extract information from the Center for Research in Security Prices (CRSP) to control for characteristics of common stocks held by insurers.

Researchers such as Schultz (2001), Campbell and Taksler (2003), Krishnan, Ritchken, and Thomson (2005), and Bessembinder, Maxwell, and Venkataraman (2006) use NAIC data for different sample periods. The data-compiling process begins with the NAIC position data. It provides year-end holding information, including insurance-company identification, bond identification, bond description, acquired date, maturity date, holding size in par, and security type. The NAIC transaction data provides insurance-company identification, bond identification, trade date, direction, price, size, and also the identification of each side of a transaction. The identification of buyer and seller is of extremely important to this research because I am able to identify trades occurred between affected and unaffected insurers. I first eliminate all data errors (e.g. negative or missing prices or par values) and all bonds with missing or incorrect CUSIPs. To be included in the bond-transaction sample, a bond transaction must involve counterparties in the secondary market. Non-secondary-market transactions include pay down, maturity, called, canceled, put, and redemption.

I then merge the position data with the transaction data to infer quarter-end holdings from year-end holdings. As a final step to compile insurer-level control variables, I merge the quarterly holding data with the NAIC InfoPro. It has detail information about insurers' financial positions and other important characteristics including states of firms' headquarters, the insurance group that an insurer belongs to, and claims paid and premium earned in each state and in each line of insurance business. To clean the data, several restrictions are applied. First, I focus on individual insurance company and exclude all pure holding companies. Second, I eliminate insurance companies that report negative direct premium written, direct premium earned, total assets, and policyholder surplus or investment positions. Such insurance companies are not viable operating entities but are retained in the database by NAIC for regulatory purposes such as the resolution of insolvencies. Finally, I winsorize by year-quarter the top and bottom 1% of the claim payments.

Security-level analysis also requires controls of security characteristics. I first collect issue credit ratings and bond characteristics (e.g. issue size, maturity) from Mergent FISD. Ratings are issued by Standard & Poor's, Moody's, and Fitch, and are combined into a single numerical rating for each bond according to the lowest rating assigned by the three rating agencies at any given point in time. Following Becker and Ivashina (2015), I also consider treasury yield spread as a control variable. I calculate the spread by deducting matched Treasury bond from promised yield to maturity. To assess whether strategic insurers earn abnormal profits, I will need to examine bond performance in secondary markets using TRACE database. I follow Bessembinder, Kahle, Maxwell, and Xu (2009) and Dick-Nielsen (2009) to clean the data. Specifically, I exclude trades that are canceled or corrected, and when multiple similar trades occur very closely in time, we discard all but one transaction (assuming they reflect a pass-through transaction). I then merge TRACE, FISD, and NAIC together and further eliminate bonds with equity features, rule144a, without offering amt and offering price; I also drop transactions where the transaction date is on/earlier than the offering date, on/later than the maturity date, or where the trading volume is larger than the offering amount.

To investigate portfolio decision of insurers, I look at cash, bond, and stock holdings. They are time t cash, bond, stock positions scaled by total invested assets at time $t\text{-}1$ respectively. I define insurers as affected if they witness rating downgrades or negative watch by rating agencies immediately after Hurricane Katrina, and at the same time, they also conduct hurricane-related insurance lines of business (e.g. homeowner insurance, commercial insurance, fire, reinsurance property) in the states of Louisiana, Mississippi, and Alabama. I also use an alternative definition by following Massa and Zhang (2017). They use Holborn Report which lists the names of general (re)insurance companies along with their 2004 market shares in the states of Louisiana, Mississippi, and Alabama, and whether they have rating or outlook changes immediately after the hurricane. Since my methodology is very similar to Holborn Report, we end up with very similar sample of affected/unaffected insurers. There are 84 affected insurers and 2,438 unaffected insurers.

[INSERT FIGURE 1 HERE]

[INSERT FIGURE 2 HERE]

Hurricane Katrina is the major event I exploit in this research. To credibly identify property damage at state-level, I adopt a major database for disasters, namely, the Spatial Hazard and Loss Database for the United States (SHELDUS). It includes hazard identification, hazard beginning and ending dates, hazard type (e.g. hurricanes, floods, tornadoes), county code, county name, state code, and property damage.[12] Figure 1 plots the disaster states declared by Federal Emergence Management Agency (FEMA) after Hurricane Katrina. The states of Louisiana, Mississppi, and Alabama are declared as disaster states. To further understand the damage for these states, I depicts daily property damage reported by SHELDUS. Figure 2 plots the property damage in $billion due to Hurricane Katrina. Consistent with FEMA, SHELDUS witnesses top three largest property damage in the states of Louisiana, Mississppi, and Alabama. August 27, 2005 will be used as the event day t=0. When data only allows quarterly observations, I use quarter three of 2005 as quarter t=+1, quarter two of 2005 as quarter t=-1, and so on.

3.2 Summary Statistics

Panel A of Table 1 reports holding-level characteristics, insurer characteristics and other variables used in the regression models. Cash, Bond, and Stock Holdings are the value of cash, bond, stock positions at quarter-end scaled by total invested assets at the previous

[12]This database is developed and provided by University of South Carolina. It only includes events that generated more than $50,000 in damage or at least one death. The database is no longer freely available and can be assessed through http://hvri.geog.sc.edu/SHELDUS/

quarter end. Unconditionally, an average insurer has 18% cash holding, 70% bond holding, and 11% stock holding. The remaining 1% includes real estate, mortgage loans on real estate, contract loans and other invested assets. The holdings in my sample are consistent with the holding information in the previous literature.

[INSERT TABLE 1 HERE]

According to Colquitt, Sommer, and Godwin (1999) and Hsu, Huang, and Lai (2015), I use insurer size, group dummy, non-invested asset holding, leverage, asset growth, cash flow variance, duration and insurers' rating as control variables in examining insurers' asset holdings. Size is the natural log of the insurer's total invested assets. Larger firms tend to have lower ratios of cash to assets (Opler, Pinkowitz, Stulz, and Williamson, 1999). Group is a dummy variable if an insurer belongs to an insurance group, and zero otherwise. When faced with liquidity shocks, members of an insurance group may have more options (e.g. capital transfers through internal capital markets) to solve the issue than a single unaffiliated insurer. Non-invested asset holding is the non-invested asset position scaled by total invested assets at the previous quarter end. Non-invested assets are the least liquid of all asset holdings and would impact the insurer's decision to hold cash. Leverage is the ratio of total liability to total assets and there is conflicting predictions on the relation between leverage and cash holdings.(Opler, Pinkowitz, Stulz, and Williamson, 1999) Asset growth proxies for investment opportunities for insurers. It is estimated as the average growth in total assets over the previous three years. Book-to-market ratio, the most common proxies for investment opportunities, may have limited use because only a subset of insurers are public insurers. Nevertheless, I also control book-to-market ratio in a sub-sample analysis for only public-listed insurers. Cash Flow Std is a proxy for volatility of insurer cash flow and is calculated as the standard deviation of total operating cash flow over the previous three years. Insurers with riskier cash flows are likely to hold more cash. Duration proxies for duration of insurers liabilities, and is estimated as the weighted average of durations reported for insurance lines, with the weights being based on each insurers unpaid losses. An insurer's need for cash depends on the payout tails for the lines of business that the insurer writes. Short tail lines, e.g. auto physical damage, financial guaranty, require a high level of liquidity since most premium income is paid out as claims in a relatively short period. Long tail lines, e.g. medical malpractice, workers' compensation will only require a low liquidity level. Finally, I use insurers rating provided by A.M.Best as a proxy for the insurer's financial strength. The highest rating is "AA+" and will be assigned 1, "A" will be assigned 2, and so on. The average rating for my sample insurers is 5.47 or between "BB+" and "A-".

Panel B of Table 1 reports bond-level characteristics. Issue size is log value of total offering amount. Bond age is log value of the age of a given bond. Bond Rating is a single numerical rating for each bond according to the lowest rating assigned by S&P, Moody's, and Fitch. Bond rating is shown to be important in affecting the insurer's transactions and portfolio decision (Ellul, Jotikasthira, and Lundblad, 2011). In my sample, the average bond is investment grade with a average rating of 7.51 or between "BBB+" and "A-". Treasury yield spread is another factor that affects the insurer's portfolio decision (Becker and Ivashina, 2015). It is computed as the spread between the yield to maturity and a matched Treasury bond.

Panel C reports the summary statistics for affected/unaffected insurers. In general, affected insurers and unaffected insurers have significantly different characteristics. This warrants a propensity score matching difference-in-difference analysis and a fixed-effect panel regression analysis controlling for all the observable variables. Compared with affected insurers, unaffected insurers are relatively smaller, hold more cash and stocks, less bonds and non-invested assets, and are less likely to be a member of an insurance group. In addition, unaffected insurers have lower cash flow risk, longer duration of liability. At bond-level, unaffected insurers are more likely to hold smaller bonds, older bonds, bonds with higher credit rating, and bonds with higher yield spreads than affected insurers.

Panel D reports the summary statistics for pre-Katrina and post-Katrina periods. All characteristics are statistically significantly different, indicating that Hurricane Katrina is a relevant event and insurers response by manipulating their portfolios, adjusting their investment preferences, or changing other financial positions. However, most of the differences are not economically significant. For example, insurers on average increase cash holding by 1% after Hurricane Katrina while the unconditional cash holding is 18%. Both ratings of insurers and ratings of bonds are decreased after Hurricane Katrina, but the economic significance is negligible. One economically significant difference is observed for yield spread. Average yield spreads increases by about 12 bps from 3.04 bps to 14.69 bps after Hurricane Katrina. This is consistent with my conjecture that bonds are sold at fire sale prices after Hurricane Katrina.

4 Main Results

In this section, I investigate the strategic motive in the insurer's transaction and portfolio decision by examining holding-level data in both univariate and difference-in-difference analysis framework (DiD), by examining transaction-level data using probit estimation, and by evaluating the insurer's investment portfolio performance and its stock performance.

4.1 Holding-level Evidence

I perform univariate and difference-in-differences analysis for cash holding, bond holding, ans stock holding. Given that different insurers may belong to the same insurance group, I estimate t-statistics based on clustered (by insurers) standard errors.

4.1.1 Univariate Analysis

Panel A of Table 2 reports the univariate test results on cash holdings of affected/unaffected insurance companies before and after Hurricane Katrina. The average quarterly holding of cash increases from 18% to 19% for unaffected insurers while it increases from 9% to 13% for affected insurers. The t-tests suggest that the increases in cash holdings are statistically significant. The 4% increase in cash holding from pre-Katrina 9% for affected insurers represent nearly 50% increase in cash holding and is economically meaningful. The 1% increase for unaffected insurers from a 18% level lacks its economic significance. The difference-in-differences estimator is -3% at 1% level of significance. It suggests that unaffected insurers are not increasing their cash holding as much as affected insurers do.

[INSERT TABLE 2 HERE]

Panel B of Table 2 reports the univariate tests results on bond holdings. Both affected and unaffected insurers significantly decrease their bond holdings after Hurricane Katrina. Unaffected insurers slightly decrease their bond holding by 1% while affected insurers decrease by 3%. Given around 70% to 80% bond holding for insurers, the decreases are not economically significant. The difference-in-differences estimator is 2% at only marginal significance. Together with the cash holding evidence in Panel A, the bond holding evidence is suggesting that unaffected insurers use cash to purchase bonds after Hurricane Katrina, potentially at fire sale prices.

Panel C of Table 2 continues the tests on stock holdings of insurers. Both affected and unaffected insurers keep their stock positions relatively stable. Affected insurers even remain the same level of holding at 8% before and after Hurricane Katrina. This may be driven by regulatory constraints on stock holdings. Insurers are required to hold a well-diversified portfolios and they can not hold stocks more than 10% of their invested assets. The regulation leaves little room for insurers to manipulate their stock holdings. It is also related to the Scholes (2000) question, namely, when faced with liquidity shocks, should financial institutions sell the liquid securities first or the illiquid securities first. Unwinding the liquid securities first will leave the institution's portfolio position illiquid and extremely vulnerable to future liquidity shocks; Liquidating the illiquid securities first makes the remaining positions more liquid but will incur large costs. The literature has not yet reach a conclusion. The preliminary evidence in Table 2 may suggest that insurers choose to liquidate the less liquid holdings of bonds first and maintain the liquid stock positions in their portfolios.

4.1.2 Difference-in-differences using Propensity Score Matching

The univariate analysis in Table 2 provides preliminary evidence of strategic portfolio management. In this subsection, I provide further evidence by controlling for insurer-level observable factors and unobservable characteristics. I employ a difference-in-differences analysis that compares the difference in asset holdings before and after Hurricane Katrina with that of a control group.

I first present a difference-in-differences research design using propensity score matching. First, I match each treatment observation with a control observation that has exactly the same group, rating, and time variable. Matching at the same time is necessary in a difference-in-differences estimation to control for calendar time effect because an economy-wide shock could occur at the same time and affect asset holdings. I require exact matches on group variable because internal capital markets are likely to be an important factor affecting asset holdings. In addition, I also require exact match on the ratings of insurers. Insurers' rating is associated with the likelihood of regulatory constraints being binding. It has been well documented in the previous literature that binding regulatory constraints have significant impacts on insurers' trading behavior (Ellul, Jotikasthira, and Lundblad, 2011). Second, I use propensity score matching on other insurer characteristics to obtain the nearest-neighbor matches. Matching is done with no replacement and a caliper of 1%.[13]

I include variables that can affect a insurer's likelihood to be unaffected and portfolio decision in the propensity score matching model. CFStd measures operating cash flow risk and I expect affected insurers to have a higher cash flow risk because they write hurricane-related insurance. Duration of insurance liability reflects the average tails for lines of business an insurer writes. Insurers with longer duration are expected to pay out premium income as claims in a relatively longer period to time, implying that lower level of cash holdings is required. Affected insurers by definition writes short-tail hurricane-related insurances business (e.g. homeowner insurance, commercial insurance, fire insurance), and thus I expect duration to have a positive effect on the likelihood of being an unaffected insurer. Larger insurers are more likely to be affected firms potentially because they self-select them into hurricane-prone areas where small insurers are unable to survive. Insurers with larger holdings of non-invested assets are more likely to be affected firms partially because affected insurers sell property insurance and majority of the non-invested assets are also real estate property.

[**INSERT TABLE 3 HERE**]

Panel A of Table 3 reports the logit regression results for the propensity score matching. As expected, the coefficient on duration is positive, the coefficients on size and non-invested

[13]The results hold if I require matching with replacement or if I do not impose a caliper

asset holdings are negative, and they are all statistically significant. The coefficient on cash flow standard deviation is negative, though statistically insignificant. I also include other insurer characteristics, e.g. an insurance group dummy and leverage ratio. An insurer within an insurance group is more likely to be an affected firm if they self-select into hurricane-prone areas. According to the literature, insurers with higher leverage are more subject to outside monitoring and face higher costs to service liabilities (Opler, Pinkowitz, Stulz, and Williamson, 1999). Affected insurers are less willing or less likely to incur these additional costs and I expect higher leverage to be associated with higher probability of being an unaffected insurers. As shown in Panel A, the coefficient on group is negative and statistically significant. The coefficient on leverage is positive and also statistically significant.

To confirm the quality of the matching, I run the same logit regression using the matched sample. The quality of the matching is ensured because none of the coefficients is significant when the matched sample is used. In addition, I directly compare the characteristics of the treatment group with that of the control group in Panel B. The results suggest that none of the characteristics of the treatment group is statistically different from that of the control group. To address the parallel trend assumption, I check the cash/bond/stock holding changes for the treatment and control group before Hurricane Katrina. As the results suggested in Panel B, no significant difference exists in cash, bond, stock holding changes between treatment and control groups before Hurricane Katrina.

Panel C shows the results of the difference-in-differences analysis. The before-and-after difference for cash holding is -2.28% and statistically significant for unaffected insurers, and it is 3.94% and statistically significant for affected insurers. The difference in differences is -6.22% and is statistically significant at 1% level of confidence. The results mean that, compared to the change in cash holdings for affected insurers with similar characteristics, unaffected insurers experience an incremental drop in quarterly cash holding of 6.22%. For bond holdings, the before-and-after difference is -2.63% for affected insurers and is only marginally significant; the difference is 3.60% for unaffected insurers ans statistically significant. The difference in differences is 6.22% and statistically significant, suggesting that relative to the change in bond holdings for affected insurers with similar characteristics, unaffected insurers witness an incremental increase in bond holding of 6.33%. Interestingly, one should note that the difference in differences for cash holding and for bond holding have very similar value but opposite sign, implying that unaffected insurers use cash to acquire bonds. Finally, the differences for stock holding are not significant. One explanation is that the stock holdings of insurers represent a very small portion of the stock market. Even a collective liquidation of stocks held by affected insurers may not be able to result in significant price discounts, leaving little opportunity for a profitable investment for unaffected insurers.

4.1.3 Difference-in-differences using Fixed Effect Panel Regressions

I first adopt a difference-in-differences estimation in the form of panel regressions with fixed effects:

$$Holding_{i,t} = \lambda_i + \lambda_t + \lambda_1 Unaffected_i + \lambda_2 PostKatrina + \lambda_3 Unaffected * PostKatrina + Controls_{i,t} + \epsilon_{i,t} \tag{1}$$

where $Holding_{i,t}$ is asset (e.g. cash, bonds, or stocks) holdings of insurer i at quarter t and is measured as quarter t cash, bonds or stocks position scaled by quarter *t-1* total invested assets. $Unaffected_i$ is a dummy variable for insurer i that equals 1 if the insurer is an unaffected insurer. $PostKatrina$ is a dummy variable that equals 1 for post-Katrina periods (2005Q3 and afterwards), and 0 otherwise. $Unaffected * PostKatrina$ is the interaction term and λ_3 is the main coefficient of interest. Control variables include total asset growth, cash flow standard deviation, duration of insurance liabilities, insurer ratings, insurer size, non-invested asset holdings, and leverage. The time-invariant dummy variable *Group* is not included because of the inclusion of insurer fixed effects. Insurer fixed effects λ_i control for time-invariant omitted insurer characteristics such as insurers' risk appetite and ensure that λ_3 reflects within-insurer changes in asset holdings instead of simply cross-sectional correlations. Time fixed effect λ_t account for transitory economy-wide factors, such as macroeconomic conditions and any time trend in insurers' asset holdings.

To illustrate the identification strategy of this difference-in-differences design, suppose a Louisiana insurer is affected by Hurricane Katrina and I want to estimate the Katrina effect on asset holdings. I can subtract the level of asset holdings before Hurricane Katrina from the level of asset holdings after Hurricane Katrina. However, economy-wide shocks (discount rates would be affected by Hurricane Katrina for example) could have occurred at the same time. To control for such factors, I calculate the same difference in a control insurer in Wyoming who is not affected by Hurricane Katrina. Finally, I calculate the difference between these two differences. Since I am interested in unaffected insurers, I compute the incremental asset holding effect of Hurricane Katrina on unaffected insurers compared with affected insurers. The tests also control for insurer-specific unobservable and observable differences and thus, are more stringent than the simple intuition provided above.

[INSERT TABLE 4 HERE]

Table 4 reports results that support the strategic motive in portfolio management. Specifically, the coefficients on $Unaffected$ in model 4 and 5 are 0.0634 and -0.044 respectively, and they are all statistically significant. They suggest that compared with affected insurers, unaffected insurers increases 6.34% cash holding while decreases 4.40% bond holding before Hurricane Katrina. The coefficients on $Unaffected * PostKatrina$ are -0.0527 and 0.0462 in model 4 and 5 respectively and are statistically significant at 1% level of confidence. They mean that compared with affected insurers, unaffected insurers increase an additional 4.62% bond holdings by using an additional 5.27% cash holdings after Hurricane Katrina. Consistent with previous evidence presented in this research, Table 4 suggests that insurers are not significantly adjusting their stock holdings around Hurricane Katrina. Consistent with prior literature, control variables have expected signs – more growth opportunities (AssetGrowth), higher cash flow risk(CFStd), higher insurer rating(Rating), smaller size (Size), lower non-invested asset holdings, and higher leverage are associated with higher cash holdings.

[INSERT FIGURE 3 HERE]

To complete the picture of the insurer's asset holdings, I depicts in Figure 3 time-series changes in quarterly cash holdings for a two-year period of [2004Q1:2006Q4]. I use my definition of affected/unaffected insurers in Panel A of Figure 3, and Massa and Zhang (2017)'s definition in Panel B of Figure 3. The two panels generate very similar pattern, suggesting my classification of insurers is consistent with prior research. In addition, Figure 3 suggests that before Hurricane Katrina in year 2004, affected and unaffected insurers follow similar trends. 2005Q1 and 2005Q2 demonstrate big increases in cash holdings for both affected and unaffected insurers. After 2005Q3, the change in cash holdings drops back to pre-Katrina level of about 3% for unaffected insurers, while it drops further to about -2% for affected insurers in 2005Q3 and 2005Q4 (most likely because of Hurricane Katrina claims) before it bounces back to steady level of approximately 3%. Together with the difference-in-differences results in Table 4, the evidence in Figure 3 for unaffected insurers confirms that big increases in 2005Q1 and 2005Q2 are immediately followed by a significant decrease in cash holdings in 2005Q3, and significant increases in bond holdings.

4.1.4 Difference-in-differences by Pre-Katrina Abnormal Cash Quartiles

This subsection digs deeper into the changes in bond holdings, and provide additional evidence that the above documented bond holding effect only concentrates on unaffected insurers who increases cash holdings the most before Hurricane Katrina.

I run model 4 of Table 4 using only unaffected insurers during the sample before 2005Q2 (e.g. $Unaffected_i$, $PostKatrina$, and $Unaffected_i * PostKatrina$ are dropped out). Since change in raw cash holding is not fully driven by discretionary behavior (e.g. strategic cash holding changes), I estimate abnormal change in cash holdings for a given insurer i at quarter t as the residual from the cross-sectional regression and assign insurers into quartiles on the basis of this value. All explanatory variables are measured contemporaneously with or before the time when cash holdings are observed, and consequently the estimation introduces no look-ahead bias.[14] Untabulated results show that all the explanatory variables have expected signs, and top and bottom quartiles are comparable for all observable characteristics. This ensures that the any differences in bond holdings are not driven by the

[14]The methodology used to define insurer abnormal cash is similar in spirit to calculating abnormal mutual fund cash (?), abnormal corporate cash (Opler, Pinkowitz, Stulz, and Williamson, 1999), abnormal chief executive officer compensation (Brick, Palmon, and Wald, 2006), and abnormal leverage (Lemmon, Roberts, and Zender, 2008).

differences in observable insurers attributes. I then re-run model 5 of Table 4 as full sample difference-in-differences fixed effect panel regressions for each quartile.

[INSERT TABLE 5 HERE]

Panel A of Table 5 reports the results by pre-Katrina raw cash holding quartiles, suggesting that the bond holding effect only concentrates on top raw cash holding quartile. Specifically, while the bottom quartile results suggest that both unaffected and affected insurers reduce bond holding after Hurricane Katrina, the top quartile suggests the opposite, namely, affected insurers increase bond holdings marginally by 2.08% while unaffected insurers significantly increase bond holdings by 5.04% after Hurricane Katrina, or an additional 2.96% increase in bond holdings. Panel B of Table 5 reports the results by pre-Katrina abnormal cash holding quartiles. As expected, when turning to abnormal cash holding quartiles, the results are getting stronger. Top abnormal cash holding quartile exhibits a statistically significant increase in bond holdings for unaffected insurers after Hurricane Katrina and a insignificant increase for affected insurers. The difference-in-differences is 3.38%, suggesting that relative to affected insurers, unaffected insurers significantly increase their bond holdings by an additional 3.38% after Hurricane Katrina.

[INSERT FIGURE 4 HERE]

To ensure that the results in Table 5 do not concentrate in any periods outside the Hurricane Katrina window, I in Figure 4 plot the time-series bond holding changes for top and bottom abnormal cash holding quartiles during the period [2004Q1:2006Q4]. The pattern confirms that, for top quartile unaffected insurers, the difference-in-differences results are most robust within 2 quarters before and 2 quarters after Hurricane Katrina. More specifically, the bond holding changes are around 2% in year 2004, become negative in 2005Q1 and 2005Q2 before increasing to about 5% in 2005Q3 and 2005Q4, after which they drop back to year-2004 level.

[INSERT TABLE 6 HERE]

Finally, to show that the documented results are not mechanical during my sample period, I run several placebo tests and report the results in Table 6. I re-run the difference-in-differences fixed-effect panel regressions for cash, bond, and stock holdings respectively but with different event quarters from 2002Q2 to 2006Q4. I explicitly drop year 2005 to avoid Hurricane Katrina effect. Due to space constraints, I only report the coefficient estimates for the difference-in-differences terms. Table 6 shows that none of the quarters in my sample period exhibits statistically significant result, though 2004 quarter 3 are marginally significant at 10% level. A further investigation suggests that in quarter 3 of 2004, there are four consecutive hurricanes (Hurricane Charley, Frances, Ivan, and Jeanne) in just one month starting from August 9 to September 13. In addition, the total damage according to SHELDUS is $30 billion which is quite comparable with $45 billion for Hurricane Katrina. In fact, on quarterly hurricane damage basis, 2004Q3 ranks as the second largest damage immediately after 2005Q3. Overall, the evidence suggests that unaffected insurers who hold the most discretionary amount of cash pre-Katrina are also the ones who significantly increase their bond holdings post-Katrina.

4.2 Transaction-level Evidence

Holding-level evidence establishes that unaffected insurers purchase bonds post-Katrina using a discretionary cash amount accumulated over the pre-Katrina period. In theory, it is the perspective of buying bonds at fire sale prices in future that attracts unaffected insurers to accumulate cash pre-Katrina. Using transaction-level data, I am able to provide additional evidence that there are bond fire sales, and these fire sales only concentrate on bonds that sold pre-Katrina and bought back post-Katrina by unaffected insurers from affected insurers.

4.2.1 Probability of Buying around Hurricane Katrina

I model the probability that an insurer will buy bonds during quarters 0 to +2 after Hurricane Katrina as a probit function:

$$Pr(P_{i,j} = 1) = \Phi(\gamma_0 + \gamma_1 I_j + \gamma_2 B_i) \tag{2}$$

where Φ denotes the standard normal distribution, $P_{i,j}$ is a dummy variable that equals one if the insurer j buys bond i during quarter [0,+2] and zero otherwise. I_j is a vector of insurer j's characteristics before Hurricane Katrina. B_i is a vector of bond i's static characteristics and time-varying characteristics at the time of Hurricane Katrina.

We include pre-Katrina cash holdings, unaffected insurer dummy, and their interaction term in I_j along with several control variables. From holding-level evidence, I expect higher pre-Katrina cash holdings to be associated with higher probability of buying bonds post-Katrina. Panel A of Table 7 reports the results for all bonds. The first two columns of Panel A reports the results for unaffected and affected insurers, respectively. The coefficient estimates are positive but only statistically significant for unaffected insurers, suggesting that given a higher pre-Katrina cash holding, unaffected insurers are more likely to purchase bonds post-Katrina. The coefficient estimate for the interaction term in column 3 is positive and statistically significant, confirming that relative to affected insurers, unaffected insurers with higher pre-Katrina cash holding are more likely to purchase bonds.

[INSERT TABLE 7 HERE]

The impact of pre-Katrina cash holdings on the probability of buying is robust to the inclusion of a host of control variables. All reported coefficient estimates are as expected. Larger insurers, and insurers with lower non-invested asset holdings, lower leverage, lower cash flow risk are more likely to purchase bonds potentially because they are less constrained in using cash. Bond-level controls suggest that insurers are more likely to purchase younger bonds, bonds with larger issue size, and bond with higher credit ratings. Edwards, Harris, and Piwowar (2007), among others, find that bid-ask spread increase with bond age and decrease with bond issue size. Consistent with Ellul, Jotikasthira, and Lundblad (2011), one interpretation of my results is that affected insurers actively try to minimize price impact by avoiding selling illiquid bonds. To provide a picture of bond purchases pre-Katrina, I repeat the tests for quarters [-2,0] and report results in the last three columns of Panel A. Both affected insurers and unaffected insurers increase cash holding by selling bonds before Katrina. As expected, the coefficient estimates for pre-Katrina cash holdings are negative and statistically significant. The coefficient for the interaction term is negative and statistically significant, suggesting that compared with affected insurers, unaffected insurers with higher cash holdings are less likely to purchase bonds. Unaffected insurers are actually more likely to sell bonds before Hurricane Katrina because they want to increase their cash holdings.

Panel B of Table 7 repeats the tests for a sub-sample of bonds where I require the same bonds sold pre-Katrina and bought back post-Katrina by unaffected insurers. Note that I only require the same bond and have not required the same bond to be traded by the same insurers. It could be the case that the bond sold by unaffected insurer A and bought back by unaffected insurer B. In Panel C of Table 7, I will further require that the same bond traded by the same insurers. This is necessary to differentiate between liquidity provision and strategic portfolio management. Insurers who strategically manage their portfolios will intentionally choose to sell and buy back the same bonds, while insurers who just want to provide liquidity do not necessarily have to trade the same bonds. I only report the coefficient estimates for $PriorCashHolding$, $Unaffeced$, and $Unaffected * PriorCashHolding$ because the the estimates for control variables are similar to those in Panel A.More specifically, Model 1 in Panel C suggests that unaffected insurers with higher pre-Katrina cash holdings are more likely to purchase back the bond they sold pre-Katrina. For affected insurers, Model 2 suggests that those with higher pre-Katrina cash holdings are less likely to purchase bonds because they have Katrina-related claims to meet. Model 3 shows that, relative to affected insurers, unaffected insurers with higher pre-Katrina cash holdings are more likely to purchase back the same bonds they sold. The results suggest that the effect we observe in Panel A concentrates on the same bonds sold and bought back by the same unaffected insurers, lending further support to the strategic portfolio management hypothesis.

4.2.2 Asset Fire Sales

Next I proceed to investigate whether the bonds purchased back by unaffected insurers are also those bonds sold by affected insurers at fire sale prices. I study cumulative abnormal returns from 45 weeks before to 45 weeks after Hurricane Katrina.To disentangle price pressure from information revelation, I follow the approach used by Coval and Stafford (2007) and Ellul, Jotikasthira, and Lundblad (2011). Specifically, I look for evidence of price declines followed by significant reversals. If the trading by affected insurers is motivated by information, then prices should drop during the period of heavy sales and stabilize permanently at the lower level. On the other hand, if affected insurers sell bonds because of liquidity needs due to Hurricane Katrina, a drop in prices should be followed by a series of positive abnormal returns compensating liquidity providers (e.g. unaffected insurers).

To measure bond returns, I first use tick-by-tick transaction data from TRACE to compute volume-weight daily bond prices and supplement the "clean" prices with accrued interests (accrued interests are from FISD matching on bond CUSIPs). I then calculate weekly bond returns as the change in the "dirty" prices from the end of a week to the end of the next week, adding in any coupons paid during the week. To estimate abnormal bond returns, I use a simple mean-adjusted model introduced by Handjinicolaou and Kalay (1984) in which an excess holding period return and a expected excess return need to be estimated first. Specifically, the excess holding-period return ($R_{excess,b}$) at time t is calculated as the bond's return (R_{bond}) minus the matched treasury return ($R_{treasury}$):

$$R^b_{excess,t} = R^b_{bond,t} - R_{treasury,t} \tag{3}$$

The mean excess return is then estimated as the average R_{excess} over the estimation period or the k weeks before the event week $t = 0$:

$$Mean(R_{excess})^b_t = \frac{1}{k}\left(\sum_{t=-1}^{-k} R^b_{excess,t}\right) \tag{4}$$

The mean-adjusted abnormal return for bond b is thus calculated as

$$AR^b_t = R^b_{excess,t} - Mean(R^b_{excess,t}) \tag{5}$$

I use week [-80,-50) as the estimation window to calculate mean excess returns and use week [-45,+45] as the event window to estimate cumulative abnormal bond returns (CAR). I calculate the median cumulative abnormal return, $MCAR$, as the median of the CARs across all bonds in a particular group that trade in each event week.

[INSERT FIGURE 5 HERE]

[INSERT TABLE 8 HERE]

To see whether the higher likelihood of being purchased back by unaffected insurers is associated with higher price discounts, I estimate probability of buying using equation 2 and calculate bond-level average probability. I then compare $MCAR$ for bonds with average buying probability in the top quartile with those for bonds with average selling probability in the bottom quartile. Figure 5 plots the $MCARs$ for the two groups by event week. Table 8 reports the MCAR by ten-week period and tests whether the $MCARs$ for the two groups are different.

Consistent with the strategic motive, Figure 5 shows that bonds that are most likely to be purchased back by unaffected insurers are also those bonds with the largest deviations from fundamental values. Table 8 further shows that the significant price discount starts from around 30 weeks before or about 2 quarters before Hurricane Katrina. From week -30 onwards, the price discount is getting larger and reaches its peak of 11.24% at event week 0. This evidence is largely consistent with holding-level evidence where I show that both affected and unaffected insurers sell bonds to accumulate cash during a two-quarter period immediately before Hurricane Katrina. The deviation is getting smaller after week 0 and nearly disappear after week 30 when prices appear to fully recover and stabilize. As bond markets are relatively less liquid than stock markets, it requires more time for prices to recover. The 30-week recovery period documented in this research is also largely consistent with previous evidence of fire sales. For example, in the study of regulation-induced bond fire sales, Ellul, Jotikasthira, and Lundblad (2011) show that it takes 30 weeks for prices to fully recover. Given the evidence so far, one plausible explanation of price recovery in the post-Katrina period is that unaffected insurers step in and provide liquidity by purchasing back the bonds they sold, eventually driving prices back to the fundamental values.

[INSERT FIGURE 6 HERE]

Although insurance companies are the major player in the U.S. bond market, not all transactions in my sample are between insurers. This introduces a concern that the fire sales I observe may not be driven by affected insurers. It might be the case where the fire sales are due to a collective sales by a large number of non-insurer investors at the same time due to other events that are not related to hurricanes at all. To address this concern, I partition my transaction sample into two sub-samples. One includes only bonds that are sold by affected insurers, while the other includes those that are sold by non-insurer investors. I then estimate CARs for these two sub-samples and plot in Figure 6. Panel A of Figure 6 plots the MCAR for bonds that are only sold by affected insurers. It suggests that the fire sales documented in Figure 6 are largely contributed by bonds sold by affected insurers. At its peak, the price discount is approximately 18%, larger than 11.24% in Figure 6. Panel B of Figure 6 plots the MCAR for bonds that are sold by non-insurer investors. It shows little evidence of fire sales for those bonds.

Since insurers' investment is likely to be geographically concentrated, it is possible that the bonds sold by affected insurers are also issued by affected corporates in Louisiana, Mississippi, and Alabama. In addition, it may also be case that bond issuers belongs to industries that are most likely to be heavily affected by hurricanes, e.g. oil, natural gas, petroleum, or airline industries. If these bonds represent a significant portion of my sample, the documented "fire sales" may merely reflect the situation in which affected corporates slowly recover over a two-quarter period after Hurricane Katrina. To address this concern, I create a sub-sample that only includes those bonds' issuers whose headquarters are located within states of Louisianan, Mississippi, and Alabama, and those issuers whose Standard Industrial Classification (SIC) codes indicate oil, gas, petroleum, or airlines industry. I identify 6,719 observations out of the full sample of 85,828 observations, implying that such bonds only represent a small part of my sample and the documented fire sales are unlikely to be driven by these transactions. Nevertheless, I re-run the probit model and the CAR test for this sub-sample of bonds.

[INSERT TABLE 9 HERE]

[INSERT FIGURE 7 HERE]

Table 9 reports the results for the probit regression using this sub-sample. Consistent with results in Table 7 for the full sample, Table 9 shows that, relative to affected insurers, unaffected insurers with higher level of pre-Katrina cash holdings are more likely to purchase bonds after Hurricane Katrina. Figure 7 plots the MCAR for this sub-sample. Similar to other bonds in the full sample, this sub-sample of bonds also exhibit some evidence of fire sales though the price discounts are smaller than those of the full sample.

Moreover, the holding-level evidence suggested that insurers do not significantly adjust their stock holdings and unaffected insurers do not significantly increase their holdings in stocks after Hurricane Katrina. As discussed briefly before, one plausible explanation is that affected insurers are not able to generate significant price pressure and price discounts in the U.S. stock market because insurance sector as a whole only hold a small part of it. To verify this conjecture, I re-run the probit model and the $MCAR$ analysis for stock transactions.

[INSERT TABLE 10 HERE]

Table 10 reports the results for the probit analysis. Consistent with holding-level evidence and my conjecture, the results in Table 10 suggest that unaffected insurers do not significantly adjust their stock holdings around Hurricane Katrina. I estimate the probability of buying stocks for unaffected insurers after Hurricane Katrina. I then calculate stock-level average buying probability and use it to assign stocks into quartiles. To compute stock abnormal returns, I first estimate expected stock returns using Carhart four-factor model (other models, Fama-french 3 factors, market and market adjusted model generate similar results) in an estimation window of 200 trading days. I require there are at least 140 daily return available within the estimation window. I also require a 50-day gap between the estimation window and the event window.

[INSERT FIGURE 8 HERE]

[INSERT FIGURE 9 HERE]

Figure 8 plots $MCARs$ for stocks with top and bottom average buying probability. Panel A of Figure 9 plots $MCAR$ for stocks that are sold by affected insurers, while Panel B of Figure 9 plots $MCAR$ for stocks that are sold by non-insurer investors. Confirming my conjecture, the figures show that there is little stock fire sale, if any, in the U.S. stock market no matter whether the stocks are sold by insurers or non-insurers. Overall, I have shown that affected and unaffected insurers sell bonds before Hurricane Katrina, introducing large price discounts in the U.S. bond market. As unaffected insurers eventually step in and provide liquidity by purchasing back the same bonds they sold, the fire sale discounts witness a steady decreases before disappearing approximately 30 weeks after Hurricane Katrina. However, the stock holdings of insurers are largely left unchanged during the Hurricane Katrina period potentially because it is very unlikely for small players like insurers to generate significant price impact in the U.S. stock market.

4.3 Performance Evidence

To complete the strategic portfolio management story, besides holding-level and transaction-level evidence, one has also to show that unaffected insurers, by acquiring bonds at fire sale prices, are able to earn abnormal profits on average. I will in this section first test the performance for the investment portfolios of insurers, and then test for a sub-sample of publicly listed insurers their public common stock performance over the Hurricane Katrina period.

4.3.1 Investment Portfolio Performance

If unaffected insurance companies have better access to underpriced bonds, one should expect to observe significant "alpha" in bond pricing models like Fama and French (1989). Using coupon rates from Mergent FISD and end-of-week volume-weighted transaction prices from TRACE, I calculate equal-weighted weekly returns on bonds acquired during the [-45, +45] event week period. I choose the [-45,+45] event week period explicitly because, as my evidence suggests, this is likely to be the period one expect to witness significant bond fire sales. On average, the excess return is positive for my full sample bonds and for several sub-samples where bonds are traded between insurers, traded by non-insurers, or where bonds are net bought/sold by unaffected insurers.

[INSERT TABLE 11 HERE]

We then turn to exposure to risk factors. A bond's realized return R, for portfolio j in week t should be given by

$$R_{j,t} = \alpha_j + R_t^F + \beta_j^R f_t^R + \beta_j^L f_t^L + \epsilon_{j,t} \tag{6}$$

where R^F is the short-term risk-free rate, f^R is the vector of risk factors and f^L contains liquidity factors. The factors should capture systematic risk component while the error term captures anything left that is idiosyncratic.

Table 11 reports the results for the factor loadings. Panel A of Table 11 provides factor loading estimation for all sample bonds in column (1), for bonds that are traded between insurers in column (2), and for bonds that are traded by non-insurers in column (3). The results suggest that insurance companies bond investment choices generate "alpha" or abnormal returns though only marginally significant for the full sample of bonds and bonds traded between insurers. In both the full sample and the sub-sample, the exposure to duration risk, credit risk, and market risk are all significantly positive, though the market risk exposure is only marginally significant.

My tests so far suggest that unaffected insurers with large pre-Katrina cash holding are likely to generate alpha by acquiring bonds at fire sale prices. Given the evidence, I further partition the full sample into several sub-samples where bonds are net bought/sold by unaffected insurers with top/bottom pre-Katrina cash holdings. Panel B reports the factor loadings for these sub-samples. Column (1) and (2) of Panel B report the results for bonds that are net bought by unaffected insurers with top and bottom pre-Katrina cash, respectively. The point estimates for α are positive and statistically significant for these two sub-samples, suggesting superior bond-picking ability or ability to generate α for unaffected insurers during the [-45,+45] event week period. Column (3) and (4) of Panel B reports the results for bonds that are net sold by unaffected insurers. As expected, the the point estimates for α are positive but insignificant, suggesting little superior ability to generate α. The estimates for other risk factors, however, are positive and significant. In other words, unaffected insurers can only generate risky returns when they net sell bonds during the [-45,+45] event week period.

The evidence of bond performance, especially the evidence for those bonds net bought by unaffected insurers, lends strong support to the strategic portfolio management hypothesis. Unaffected insurers are able to generate α because, by strategically selling bonds and purchasing back after Hurricane Katrina, they establish better access to underpriced bonds than affected insurers. Affected insurers would have no choice but to sell bonds at fire sale prices.

4.3.2 Publicly Listed Insurers' Stock Performance

If unaffected insurers are able to generate significant abnormal returns for their shareholders, I should also expect to see positive stock price reaction for these insurers. Not all insurers are public-listed insurers. In this section, I examine the risk-adjusted returns for only public-listed unaffected insurers after controlling for the factor loadings using the capital asset pricing model, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model including Carhart (1997) model and the Pástor and Stambaugh (2003) liquidity factor. To assemble the stock price sample for public insurers, I use the Center for Research in Security Prices (CRSP) database to identify all publicly traded insurers during the [-45,+45] event week period.[15]. This yields 659 insurers, including 244 life insurers.

[INSERT TABLE 12 HERE]

Column (1) of Table 12 reports the α estimates for all non-life insurers. I separate life and non-life insurers because life insurers are similar to unaffected general insurers in the sense that they are also not affected by Hurricane Katrina (e.g. limited number of people are reported dead or missing). I will test life insurers' stock performance separately in Table 13. The α estimates using the four models for all non-life insurers are all insignificant. In column (2) and column (3), I partition the non-life insurer sample in column (1) into a affected insurer sample in column (2) and a unaffected insurer sample in column (3) and report the results for α estimates. Matching affected insurers to CRSP requires manually

[15]Insurers are firms with SIC codes of 6311 (life insurance), 6321 (accident and health insurance), 6324 (hospital and medical service plans), 6331 (fire, marine, and casualty insurance), 6351 (surety insurance), 6361 (title insurance), 6399 (insurance carriers), and 6411 (insurance agents, brokers, and services)

check the name of the insurance companies. Out of the total 84 affected insurance companies in my original sample, I am able to identify 80 firms. Results in column (2) and column (3) suggest that the non-significant α estimates are mainly driven by the affected insurer sample; for the unaffected insurer sample, the α estimates are significantly positive for Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and the five-factor model including Carhart (1997) model and the Pástor and Stambaugh (2003) liquidity factor.

I then further partition the sample of unaffected insurers into unaffected insurers with top quartile pre-Katrina cash holding and those with bottom quartile pre-Katrina cash holdings. This again requires manual matching by insurers' names. My original sample of unaffected insurers have 412 firms in the top quartile and another 412 firms in the bottom quartile. However, I can only match 45 firms in the top quartile and 24 firms in the bottom quartile. Given the poor matching, results in column (4) and (5) in Table 12 have mixed results. For example, while the five-factor model suggests that top cash quartile unaffected firms outperform bottom cash quartile firms, the Fama and French (1993) three-factor model and Carhart (1997) four-factor model suggest the opposite. Nevertheless, the results for unaffected insurers suggest that they are earning significant positive α in the stock market for their shareholders.

[INSERT TABLE 13 HERE]

[INSERT FIGURE 10 HERE]

I next turn to the life insurer sample. Table 13 reports the α estimates and loadings on other risk factors. Except the market model in column (1) of Table 13, all other three models (Fama and French (1993), Carhart (1997), and Carhart (1997) augmented with the Pástor and Stambaugh (2003) liquidity factor) report positive and statistically significant αs, suggesting that, like unaffected insurers, life insurers are also able to generate α. Figure 10 plots the life insurers' net sales for those bonds net purchased by unaffected insurers during a [-8,+8] event-quarter period. The preliminary evidence in Figure 10 suggests that the α generated by life insurers are probably due to purchasing bonds at fire sale prices after Hurricane Katrina. However, due to data limitation, I am not able to verify this conjecture at this stage. Future research may use transaction-level data to further explore the trading behavior of life insurance companies.

5 Robustness

This section runs robustness checks. I first address survivorship bias by examining an announced hurricane that did not make landfill – the Hurricane Flossie in 2007. I next further differentiate between liquidity provision and strategic portfolio management.

5.1 The Announced Hurricane that Did Not Make Landfill

This section address potential survivorship bias. I use Hurricane Flossie as the event of study and repeat the analysis. Flossie originated from a tropical wave that emerged off Africa on July 21, 2007. It entered the eastern Pacific on August 1 and became a tropical depression and a tropical storm shortly thereafter on August 8. On August 11, Flossie became a major hurricane, but quickly deteriorated to a tropical depression by August 16, 2007. Given the timeline, I use August 8 as the event day 0.

In theory, one should expect insurers increase their cash holding before an announced hurricane. While affected insurers sell bonds, unaffected insurers sell and purchase back to earn abnormal profits. To identify affected and unaffected insurers, previous literature and I use ex-post information. In other words, we know an insurer is an affected insurer only when a hurricane affects the insurer and then we look backwards to examine its portfolio decision before the hurricane. For hurricanes like Hurricane Flossie, we need to predict ex-ante which insurers will be affected. The best prediction one can make is to use geographic information of insurers and past information about similar hurricanes. In the case of Hurricane Flossie, the state most likely to be affected is the state of Hawaii. However, there are few insurers located in Hawaii, leading to inadequate observations for most regression analysis. Nevertheless, I examine bond MCAR around Hurricane Flossie because if affected insurers liquidate their bond holdings aggressively one should expect to observe price impacts.

[INSERT FIGURE 11 HERE]

[INSERT FIGURE 12 HERE]

Figure 11 plots the MCAR for bonds traded by insurers during the [-45,+45] event-week period. I assume all insurers except for Hawaii insurers are unaffected insurers and run the probit model using equation 2 and Bonds are then assigned into top quartile and bottom quartile buying probability groups. As seen in Figure 11, there is no evidence of significant price discount during the [-45,+45] event week period. In fact, bonds with top buying probability exhibit slightly higher MCAR than those with bottom buying probability, suggesting that the Hurricane Flossie did not drive affected insurers (or Hawaii insurers) to significantly reduce their bond holdings. To provide further evidence, I plot quarterly changes in cash holdings for all unaffected insurers around Hurricane Flossie in Figure 12. Again, there is no evidence of significant portfolio management probably because the hurricane is quickly deteriorated within 1 week (August 11 to August 16).

5.2 Liquidity Provision or Strategic Portfolio Management

An alternative explanation for my observation is a liquidity provision story, namely, unaffected insurers side aside capital and provide liquidity post-Katrina when bonds are transacted at fire sale prices. I showed in section 4.2 that unaffected insurers sell and buy back the same bond from affected insurers after Hurricane Katrina. This section provides further evidence to differentiate between liquidity provision and strategic portfolio management.

If liquidity provision story works, one should expect to observe the most significant results for a subsample of insurers where the affected and unaffected insurers belongs to the same insurance group. Relative to stand-along insurers or insurers in different insurance groups, it is more likely for insurers in the same group to help each other by providing liquidity when it is most needed. I re-run the difference-in-differences fixed-effect panel regressions on different asset holdings for this sub-sample of insurers and present the results in Table 14.

[INSERT TABLE 14 HERE]

With or without controls, all the six models in Table 14 suggest statistically insignificant results for the difference-in-differences estimators. It means that liquidity provision story is unlikely, lending further support to the strategic portfolio management hypothesis.

6 Conclusion

By exploiting Hurricane Katrina, this paper finds that unaffected insurers sell bonds pre-Katrina and buy back the same bonds from affected insurers at fire sale prices post-Katrina. The unaffected insurers' bond investment portfolios earn significantly positive α after controlling for stock market risk, credit risk, and duration risk. The α concentrates only on bonds that are net purchased by unaffected insurers. Further analysis on a sub-sample of publicly listed insurers' stock prices suggests that unaffected insurers also earn α for their shareholders in the stock market, after controlling for Carhart (1997) four factors and the Pástor and Stambaugh (2003) liquidity factor. Overall, the evidence is consistent with strategic portfolio management hypothesis for insurance companies, at least for the [-45,+45] event week period or roughly [2004Q4 : 2006Q2]. It is also robust to survivorship bias and a liquidity provision story.

Several related papers emerged recently. Simutin (2014) studies abnormal cash holdings for mutual funds and finds that high abnormal cash mutual fund outperform low abnormal cash peers. It concludes that abnormal cash provides financial flexibility. Becker and Ivashina (2015) find insurers reach for yield in choosing their investments for the 2004Q1 to 2010Q3 period. They conclude that the higher yields reflect market risk rather than superior bond picking or better access to underpriced bonds. This paper provides an important and meaningful supplement to the literature. I show that one of the mechanism through which the Simutin (2014)'s "financial flexibility" may work is to strategically increase cash holdings by selling illiquid assets and purchase back the same assets after liquidity shocks at fire sale prices. One explanation for Becker and Ivashina (2015) to find no evidence of αs for insurers is that the sample period is longer. Indeed, untabulated results also suggest no evidence for α outside my sample period using my sample insurers.

References

Acharya, Viral V, Heitor Almeida, and Murillo Campello, 2007, Is cash negative debt? a hedging perspective on corporate financial policies, *Journal of Financial Intermediation* 16, 515–554.

Acharya, Viral V, Denis Gromb, and Tanju Yorulmazer, 2012, Imperfect competition in the interbank market for liquidity as a rationale for central banking, *American Economic Journal: Macroeconomics* 4, 184–217.

Acharya, Viral V, and Ouarda Merrouche, 2012, Precautionary hoarding of liquidity and interbank markets: Evidence from the subprime crisis, *Review of Finance* p. 22.

Acharya, Viral V, Hyun Song Shin, and Tanju Yorulmazer, 2011, Crisis resolution and bank liquidity, *Review of Financial Studies* 24, 2166–2205.

Acharya, Viral V, and David Skeie, 2011, A model of liquidity hoarding and term premia in inter-bank markets, *Journal of Monetary Economics* 58, 436–447.

Ashcraft, Adam, James McAndrews, and David Skeie, 2011, Precautionary reserves and the interbank market, *Journal of Money, Credit and Banking* 43, 311–348.

Beaver, William H, Maureen F McNichols, and Karen K Nelson, 2003, Management of the loss reserve accrual and the distribution of earnings in the property-casualty insurance industry, *Journal of Accounting and Economics* 35, 347–376.

Becker, Bo, and Victoria Ivashina, 2015, Reaching for yield in the bond market, *The Journal of Finance* 70, 1863–1902.

Becker, Bo, and Marcus Opp, 2013, Regulatory reform and risk-taking: Replacing ratings, Discussion paper, National Bureau of Economic Research.

Bessembinder, Hendrik, Kathleen M Kahle, William F Maxwell, and Danielle Xu, 2009, Measuring abnormal bond performance, *Review of Financial Studies* 22, 4219–4258.

Bessembinder, Hendrik, William Maxwell, and Kumar Venkataraman, 2006, Market transparency, liquidity externalities, and institutional trading costs in corporate bonds, *Journal of Financial Economics* 82, 251–288.

Brick, Ivan E, Oded Palmon, and John K Wald, 2006, Ceo compensation, director compensation, and firm performance: Evidence of cronyism?, *Journal of Corporate Finance* 12, 403–423.

Cai, Fang, 2009, Trader exploitation of order flow information during the ltcm crisis, *Journal of Financial Research* 32, 261–284.

Campbell, John Y, and Glen B Taksler, 2003, Equity volatility and corporate bond yields, *The Journal of Finance* 58, 2321–2350.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cleveland, Harold B, and Thomas F Huertas, 1985, *Citibank 1812-1970* (Cambridge, MA: Harvard University Press).

Colquitt, L Lee, David W Sommer, and Norman H Godwin, 1999, Determinants of cash holdings by property-liability insurers, *Journal of Risk and Insurance* pp. 401–415.

Cornett, Marcia Millon, Jamie John McNutt, Philip E Strahan, and Hassan Tehranian, 2011, Liquidity risk management and credit supply in the financial crisis, *Journal of Financial Economics* 101, 297–312.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Diamond, Douglas W, and Raghuram G Rajan, 2011, Fear of fire sales, illiquidity seeking, and credit freezes, *The Quarterly Journal of Economics* 126, 557–591.

Dick-Nielsen, Jens, 2009, Liquidity biases in trace, *The Journal of Fixed Income* 19, 43.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *The Journal of finance* 65, 1237–1267.

Edwards, Amy K, Lawrence E Harris, and Michael S Piwowar, 2007, Corporate bond market transaction costs and transparency, *The Journal of Finance* 62, 1421–1451.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

———, and Yihui Wang, 2012, Is historical cost accounting a panacea? market stress, incentive distortions, and gains trading, Discussion paper, Unpublished Working Paper.

Fama, Eugene F, and Kenneth R French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of financial economics* 25, 23–49.

———, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Froot, Kenneth A, David S Scharfstein, and Jeremy C Stein, 1993, Risk management: Coordinating corporate investment and financing policies, *the Journal of Finance* 48, 1629–1658.

Gale, Douglas, and Tanju Yorulmazer, 2013, Liquidity hoarding, *Theoretical Economics* 8, 291–324.

Gaver, Jennifer J, and Jeffrey S Paterson, 2004, Do insurers manipulate loss reserves to mask solvency problems?, *Journal of Accounting and Economics* 37, 393–416.

Handjinicolaou, George, and Avner Kalay, 1984, Wealth redistributions or changes in firm value : An analysis of returns to bondholders and stockholders around dividend announcements, *Journal of Financial Economics* 13, 35–63.

Harrington, Scott E, and Patricia M Danzon, 1994, Price cutting in liability insurance markets, *Journal of Business* pp. 511–538.

Hsu, Wen-Yen, Yenyu Huang, and Gene Lai, 2015, Corporate governance and cash holdings: evidence from the us property–liability insurance industry, *Journal of Risk and Insurance* 82, 715–748.

Keynes, John Maynard, 1936, *The General Theory of Employment, Interest and Money* (Macmillan Cambridge University Press).

Koijen, Ralph SJ, and Motohiro Yogo, 2015, The cost of financial frictions for life insurers, *The American Economic Review* 104.

——— , 2016, Shadow insurance, *Econometrica* 84, 1265 – 1287.

Krishnan, CNV, Peter H Ritchken, and James B Thomson, 2005, Monitoring and controlling bank risk: Does risky debt help?, *The Journal of Finance* 60, 343–378.

Lemmon, Michael L, Michael R Roberts, and Jaime F Zender, 2008, Back to the beginning: persistence and the cross-section of corporate capital structure, *The Journal of Finance* 63, 1575–1608.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda, 2012, The role of institutional investors in propagating the crisis of 2007–2008, *Journal of Financial Economics* 104, 491–518.

Massa, Massimo, and Lei Zhang, 2017, The spillover effects of hurricane katrina on corporate bonds and the choice between bank and bond financing, .

Merrill, Craig B, Taylor D Nadauld, René M Stulz, and Shane Sherlund, 2012, Did capital requirements and fair value accounting spark fire sales in distressed mortgage-backed securities?, Discussion paper, National Bureau of Economic Research.

Merrill, Craig B, Taylor D Nadauld, René M Stulz, and Shane M Sherlund, 2013, Were there fire sales in the RMBS market?, *The Economist*.

NAIC, Capital Market Special Reports, 2011, Insurance asset management: Internal, external or both?, Discussion paper, National Association of Insurance Commissioners (NAIC).

Opler, Tim, Lee Pinkowitz, René Stulz, and Rohan Williamson, 1999, The determinants and implications of corporate cash holdings, *Journal of Financial Economics* 52, 3–46.

Pástor, L'uboš, and Robert F Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Petroni, Kathy Ruby, 1992, Optimistic reporting in the property-casualty insurance industry, *Journal of Accounting and Economics* 15, 485–508.

Scholes, Myron S, 2000, Crisis and risk management, *American Economic Review* pp. 17–21.

Schultz, Paul, 2001, Corporate bond trading costs: A peek behind the curtain, *The Journal of Finance* 56, 677–698.

Simutin, Mikhail, 2014, Cash holdings and mutual fund performance, *Review of Finance* 18, 1425–1464.

Weiss, Mary, 1985, A multivariate analysis of loss reserving estimates in property-liability insurers, *Journal of Risk and Insurance* pp. 199–221.

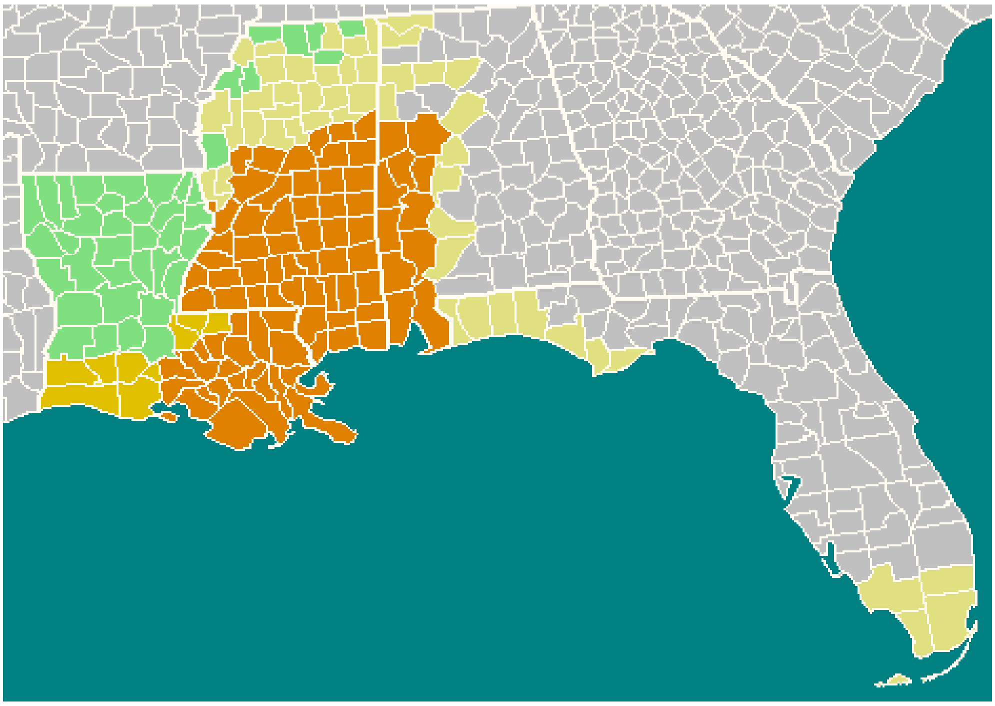


Figure 1: Declared Disaster States After Hurricane Katrina. This map presents the disaster states declared by Federal Emergence Management Agency (FEMA) after Hurricane Katrina.

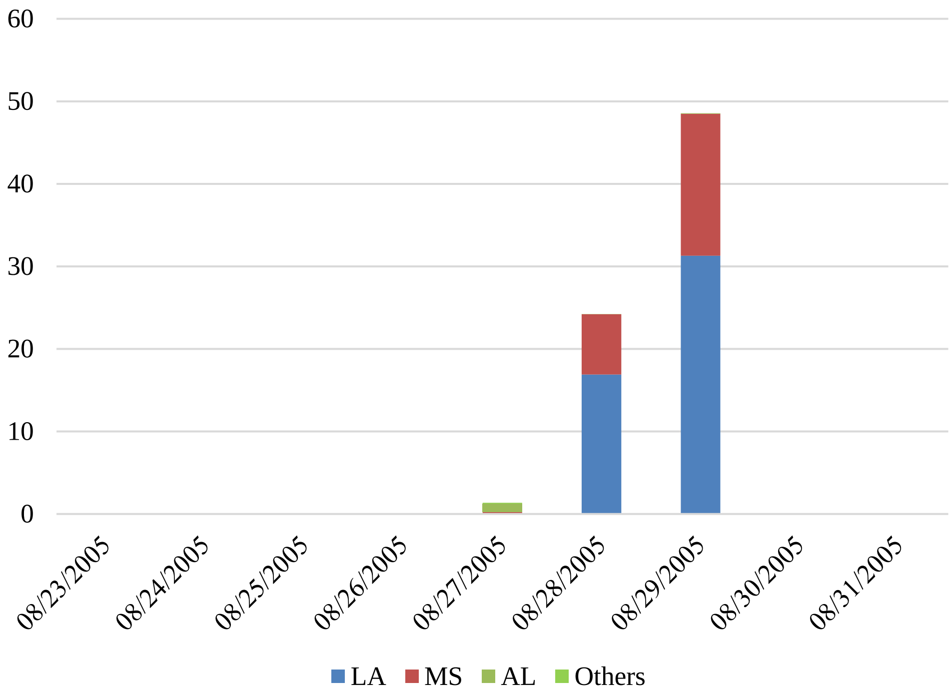
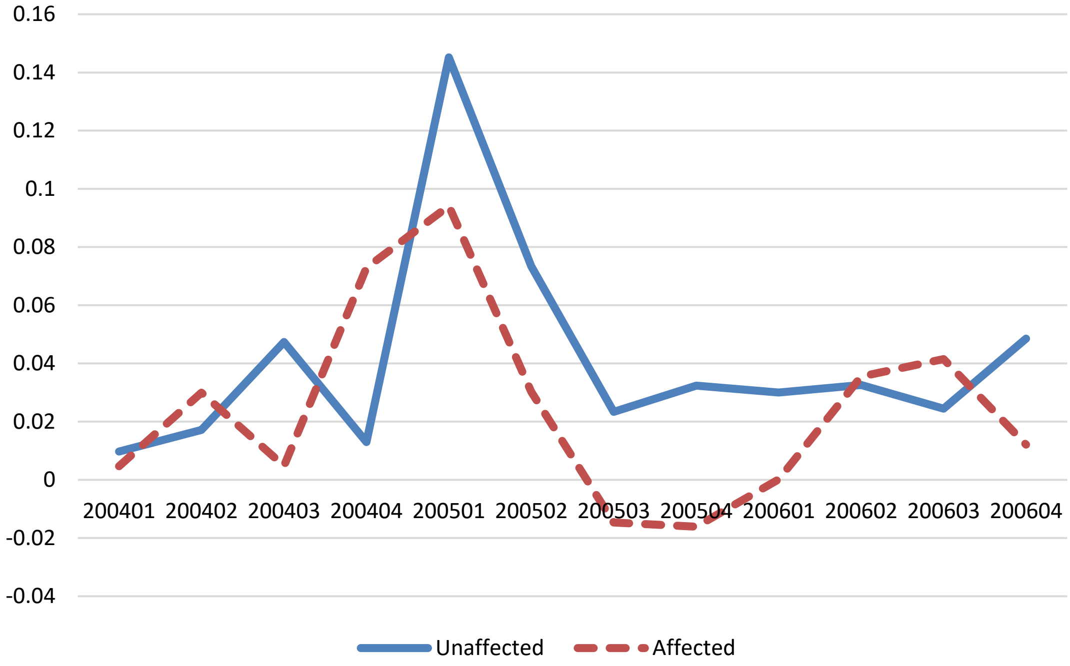


Figure 2: Property Damage in $billion Due to Hurricane Katrina. This figure depicts the daily property damage reported by Spatial Hazard Events and Losses (SHELDUS) database at the University of South Carolina.

Panel A: Change in Cash Holdings by my Definition of Affected/Unaffected Insurers



Panel B: Change in Cash Holdings by Messa and Zhang (2017) definition

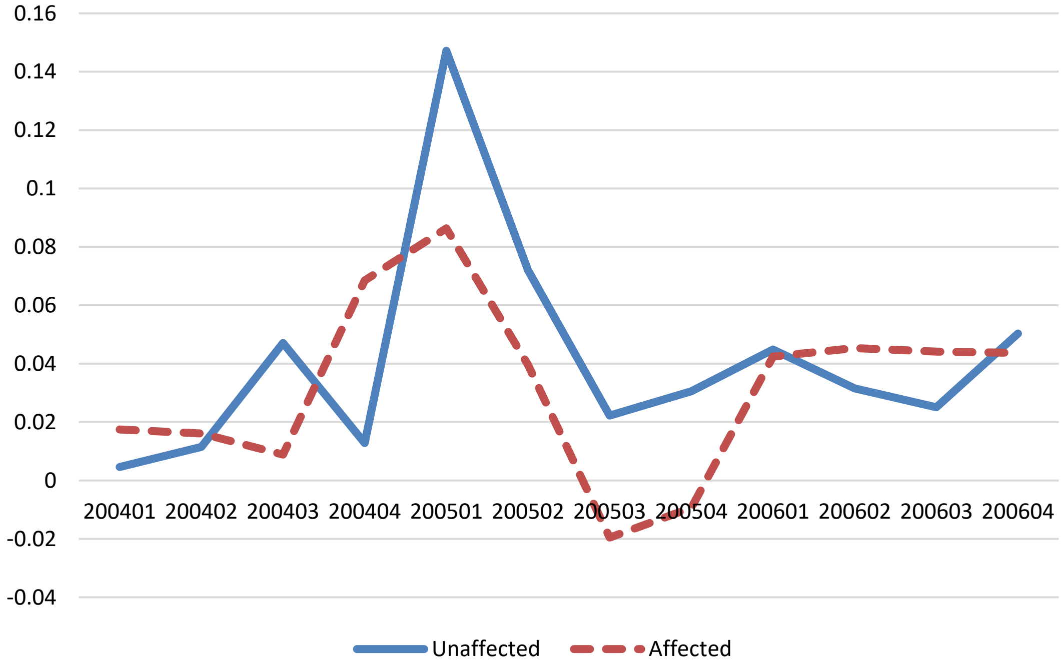
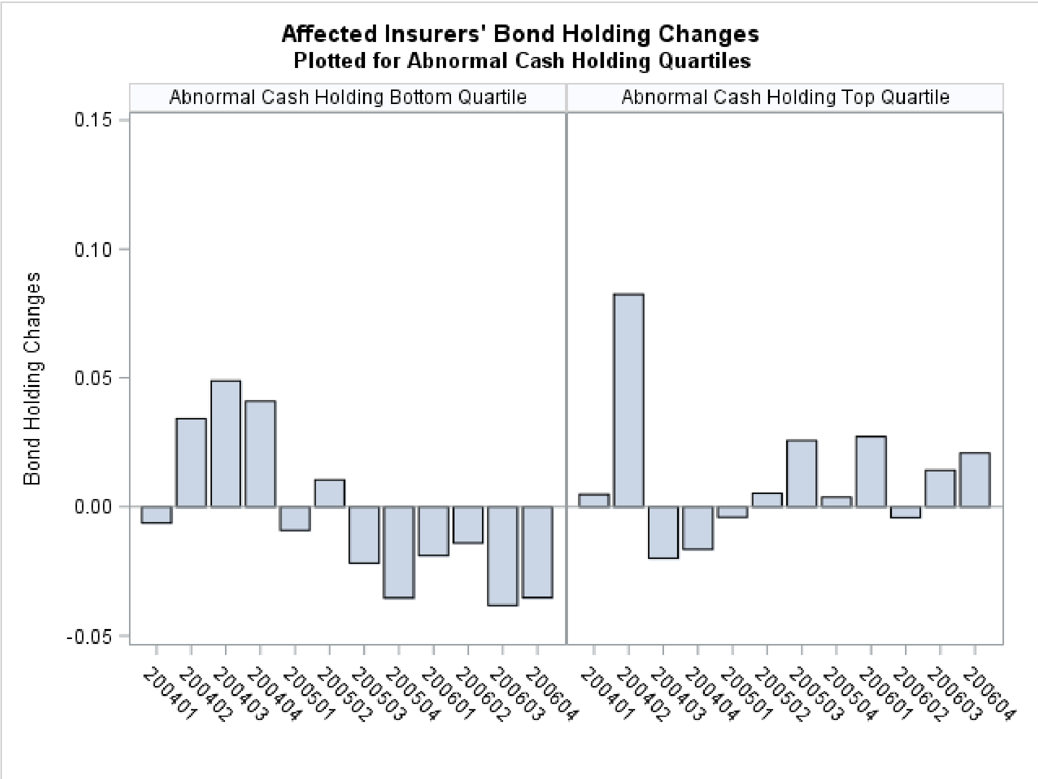


Figure 3: Average Change in Cash Holdings. Change in cash holdings is computed as the difference between quarter *t* and quarter *t-1* cash balance scaled by total invested assets at quarter *t-1*. Two methods to identify affected/unaffected insurers: 1) my definition where I define insurers as affected if they witness rating downgrades or negative watches immediately after Hurricane Katrina 2) Massa and Zhang (2017) defines affected insurers according to the Holborn Report. The Holborn Report uses a very similar methodology and thus the identified insurers are also very similar.



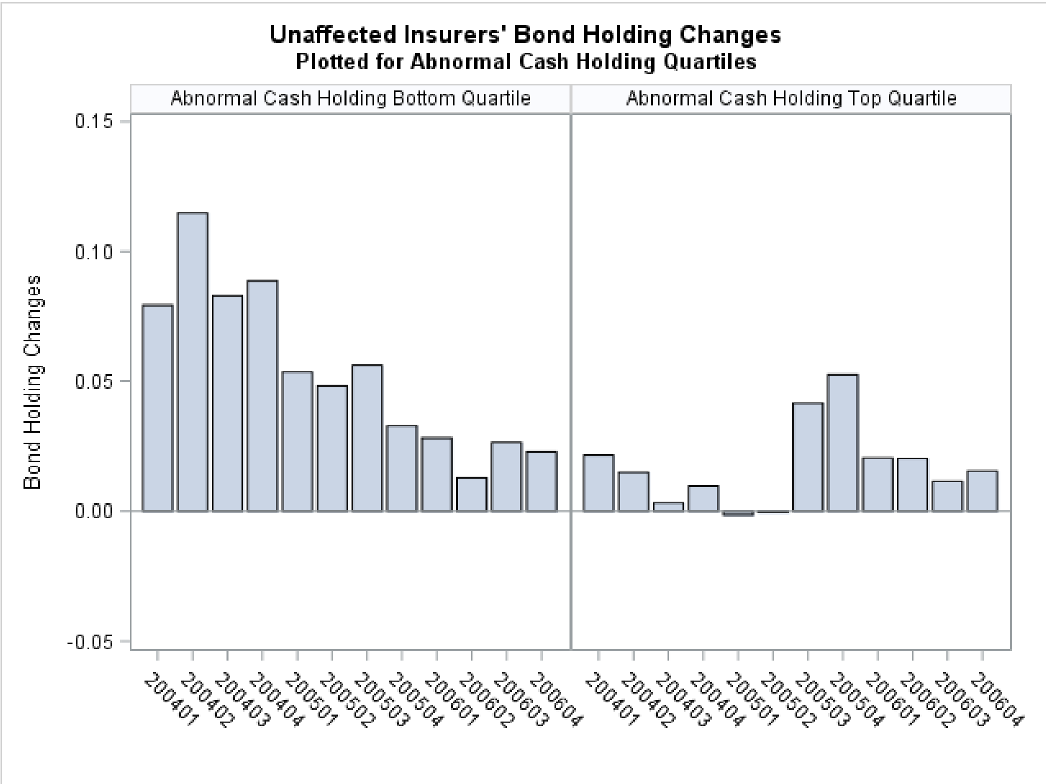


Figure 4: Average Change in Bond Holdings by Pre-Katrina Cash Quartiles. I sort insurers according to their pre-Katrina abnormal cash holdings into quartiles. The abnormal cash holding is estimated as the residual from a regression where raw cash holding is regressed on several firm characteristics. The change in bond holding is computed as the difference between quarter *t* and quarter *t-1* bond position scaled by total invested assets at quarter *t-1*.

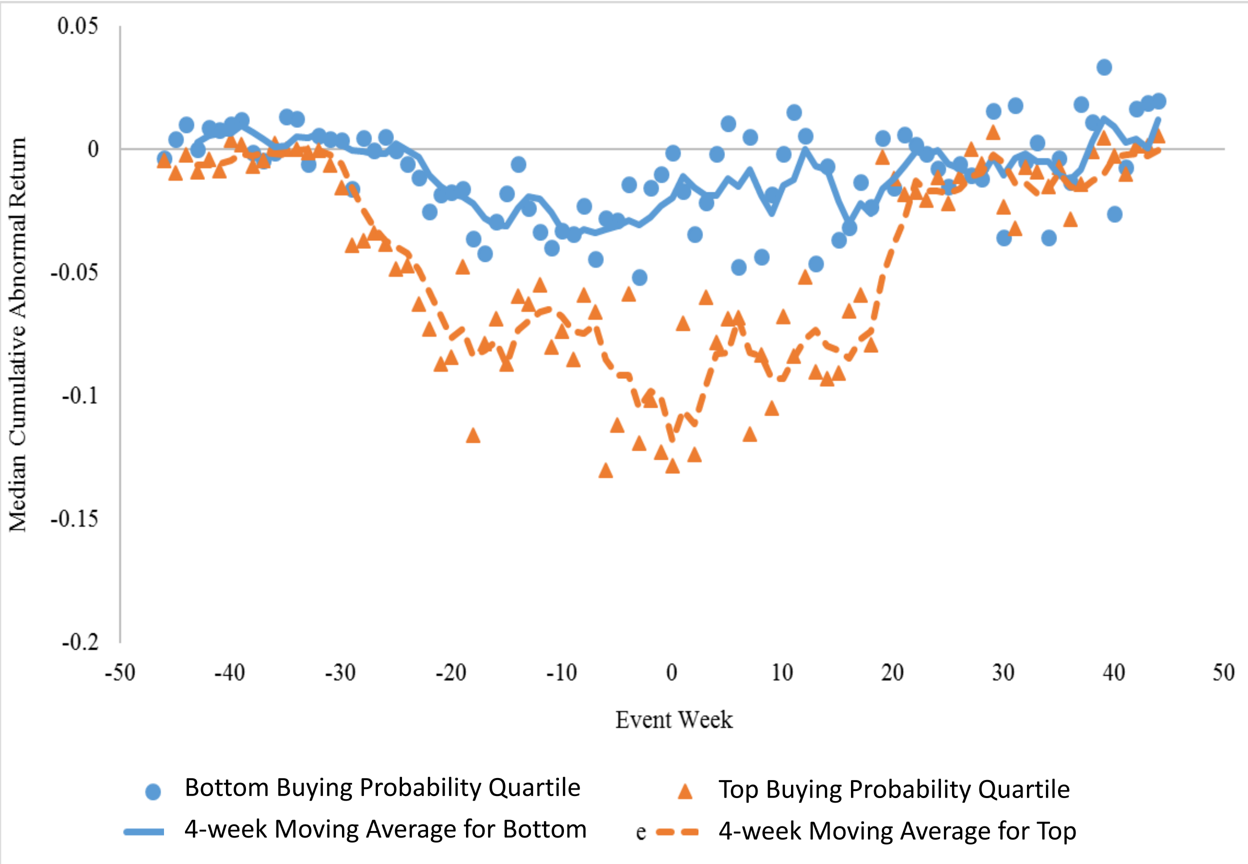


Figure 5: Bond Median Cumulative Abnormal Returns (MCAR) by average Buying Probability. To measure bond returns, I first use tick-by-tick transaction data from TRACE to compute volume-weight daily bond prices and supplement the "clean" prices with accrued interests (accrued interests are from FISD matching on bond CUSIPs). I then calculate weekly bond returns as the change in the "dirty" prices from the end of a week to the end of the next week, adding in any coupons paid during the week. To estimate abnormal bond returns, I use a simple mean-adjusted model in which an excess holding period return and an expected excess return need to be estimated first. I use week [-80,-50) as the estimation window to calculate mean excess returns and use week [-45,+45] as the event window to estimate cumulative abnormal bond returns (CAR). I calculate the median cumulative abnormal return, *MCAR,* as the median of the CARs across all bonds in a particular group that trade in each event week. I model the probability that an insurer will buy bonds during quarters 0 to +2 after Hurricane Katrina as a probit function where the dependent variable is a dummy variable that equals one if an insurer buys bond during quarter [0,+2] and zero otherwise. The independent variables include several insurer characteristics and bond characteristics. According to the estimated bond-level average buying probability, I then sort bonds into quartiles. Finally, I plot the MCAR for the top quartile and bottom quartile bonds.

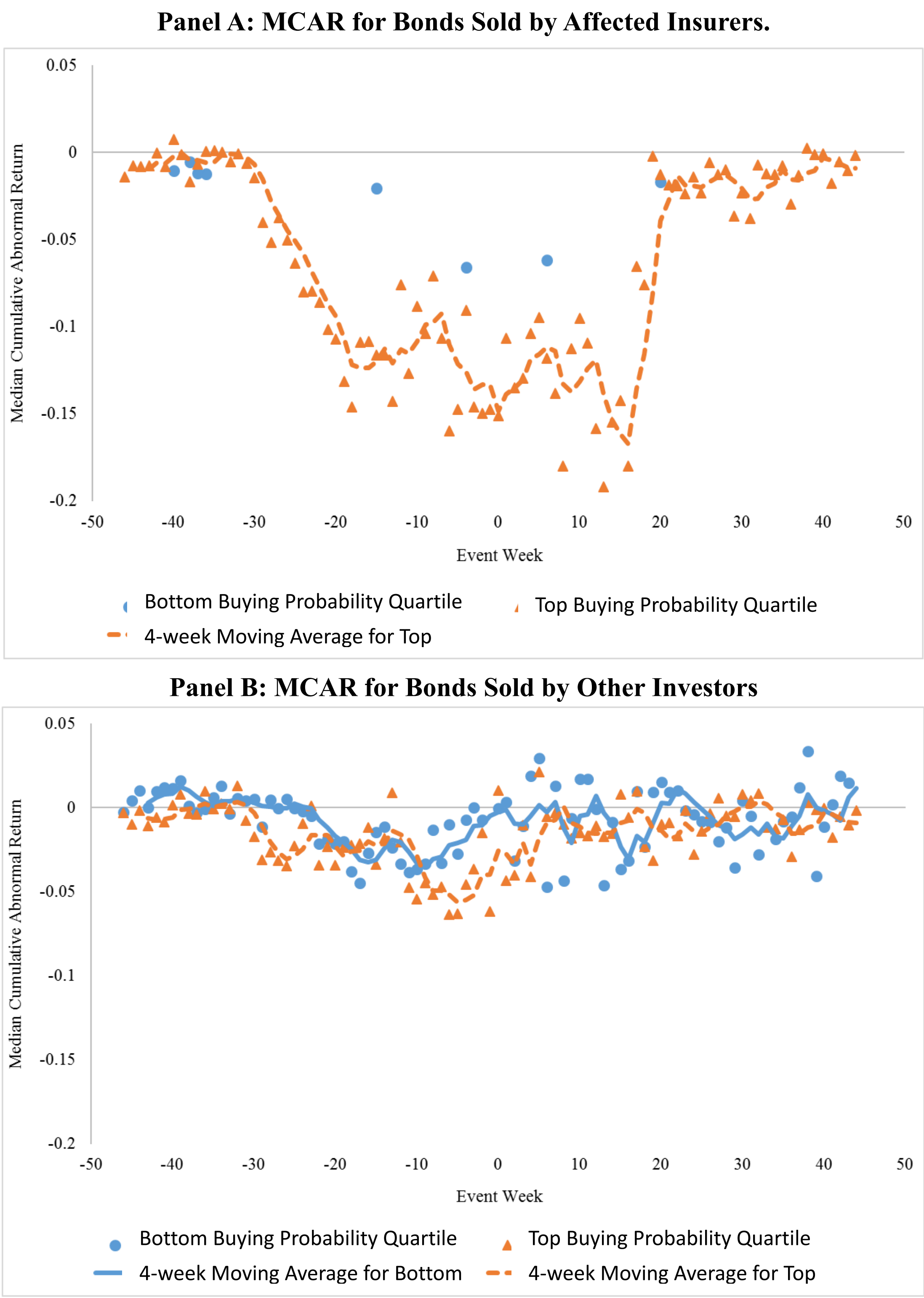


Figure 6: MACAR for Bonds when they are Sold by Different Investors. We take the sample in Figure 5 and partition the sample into two sub-samples according to the investor's identification of the other side of the transaction. Panel A presents the MCAR for those bonds that are sold by affected insurers. Panel B presents the MCAR for those bonds sold by all other investors. For each sample, similar to Figure 5, I present the MCAR for top and bottom buying probability quartiles. The probability estimation and the MCAR calculation are the same as those used in Figure 5.

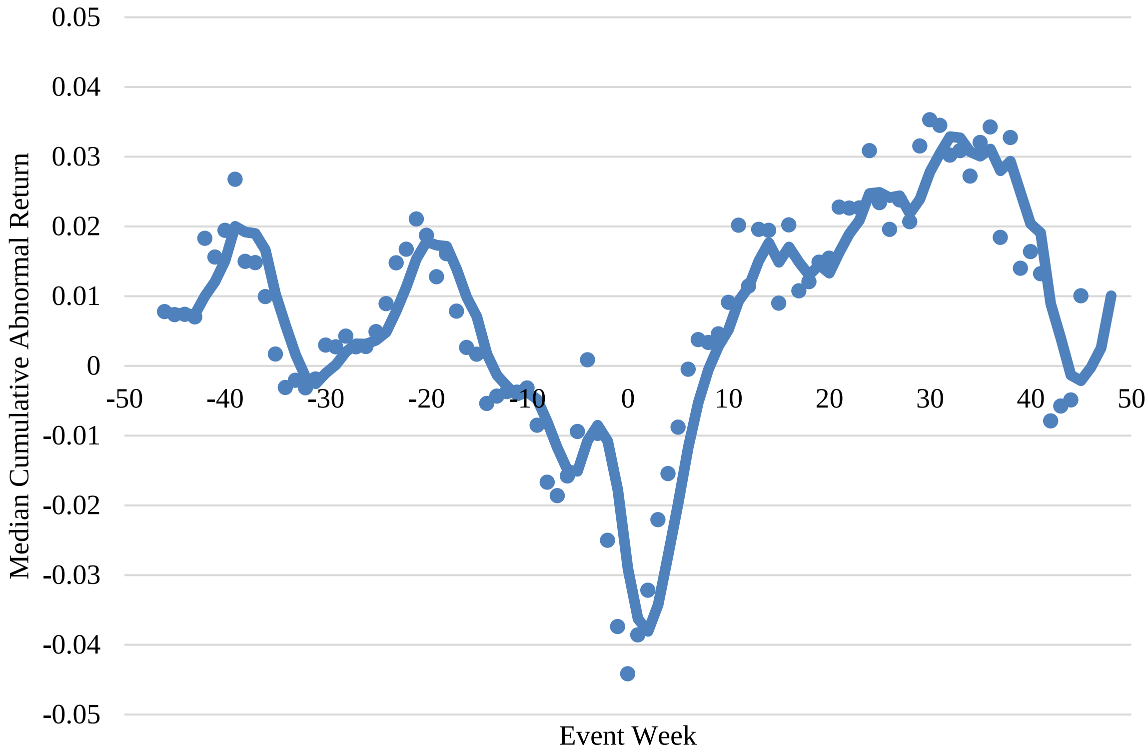


Figure 7: Bond Median Cumulative Abnormal Returns (MCAR) for Affected Issuers. We define a bond issuer is affected if the issuer's headquarter is located in one of the states of Alabama, Mississippi, Louisiana, or if the issuer is in industries that are related to natural oil, gas, petroleum, or airlines. Given the small sample size, I am not able to depict MCAR by buying probability quartiles. I include all bonds issued by affected issuers during the [-45,+45] event-week period. The method to compute MCAR is the same as the method used in Figure 5

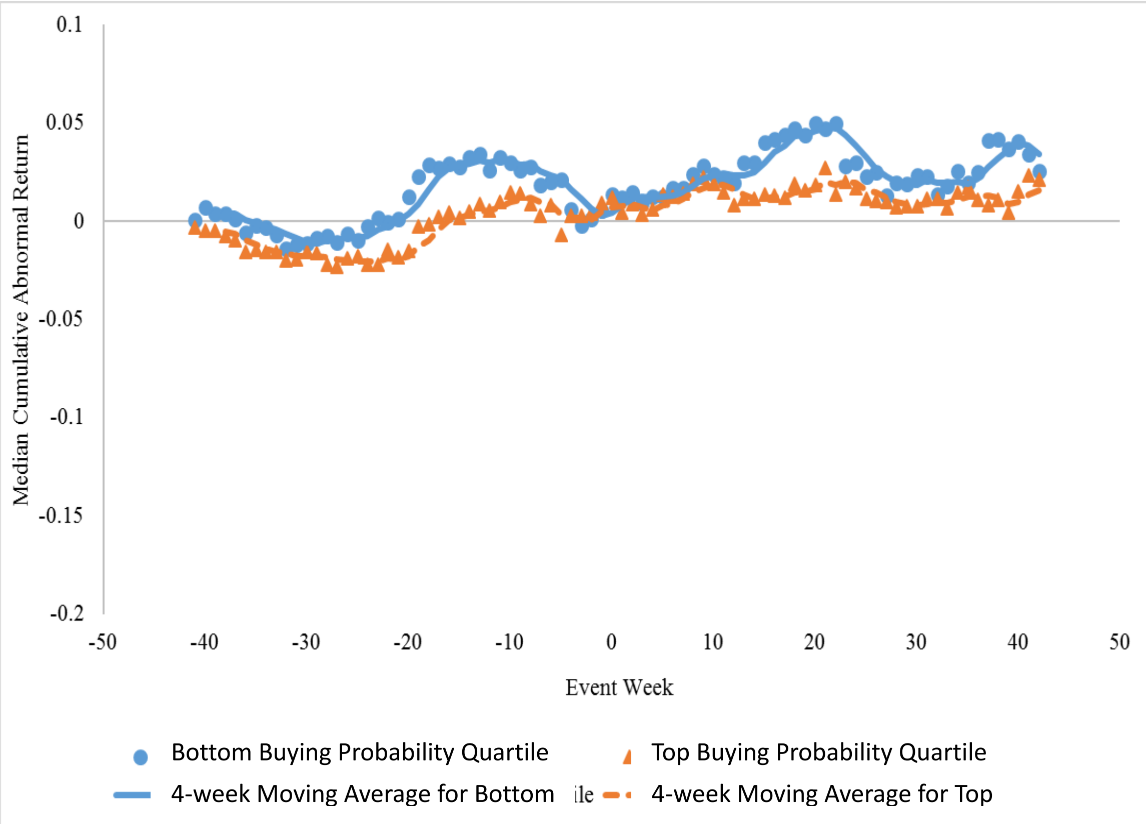
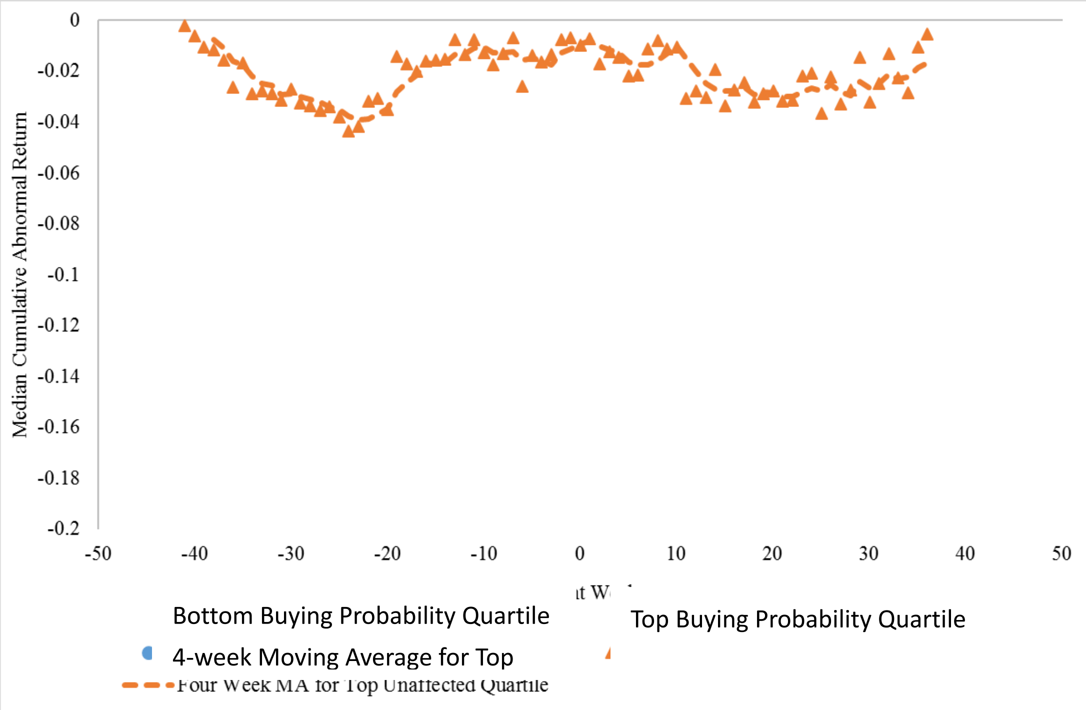


Figure 8: MCAR for Stocks by Probability of Buying. To compute stock abnormal returns, I first estimate expected stock returns using Carhart four-factor model (other models, Fama-french 3 factors, market and market adjusted model generate similar results) in an estimation window of 200 trading days. I require there are at least 140 daily return available within the estimation window. I also require a 50-day gap between the estimation window and the event window of [-45,+45] event-week. I calculate the median cumulative abnormal return, *MCAR,* as the median of the CARs across all stocks in a particular group that trade in each event week. I model the probability that an insurer will buy stocks during quarters 0 to +2 after Hurricane Katrina as a probit function where the dependent variable is a dummy variable that equals one if an insurer buys bond during quarter [0,+2] and zero otherwise. The independent variables include several insurer characteristics and Carhart four factors. According to the estimated stock-level average buying probability, I then sort stock into quartiles. Finally, I plot the MCAR for the top quartile and bottom quartile stocks.

Panel A: MCAR for Stocks Sold by Affected Insurers.



Panel B: MCAR for Stocks sold by Other Investors.

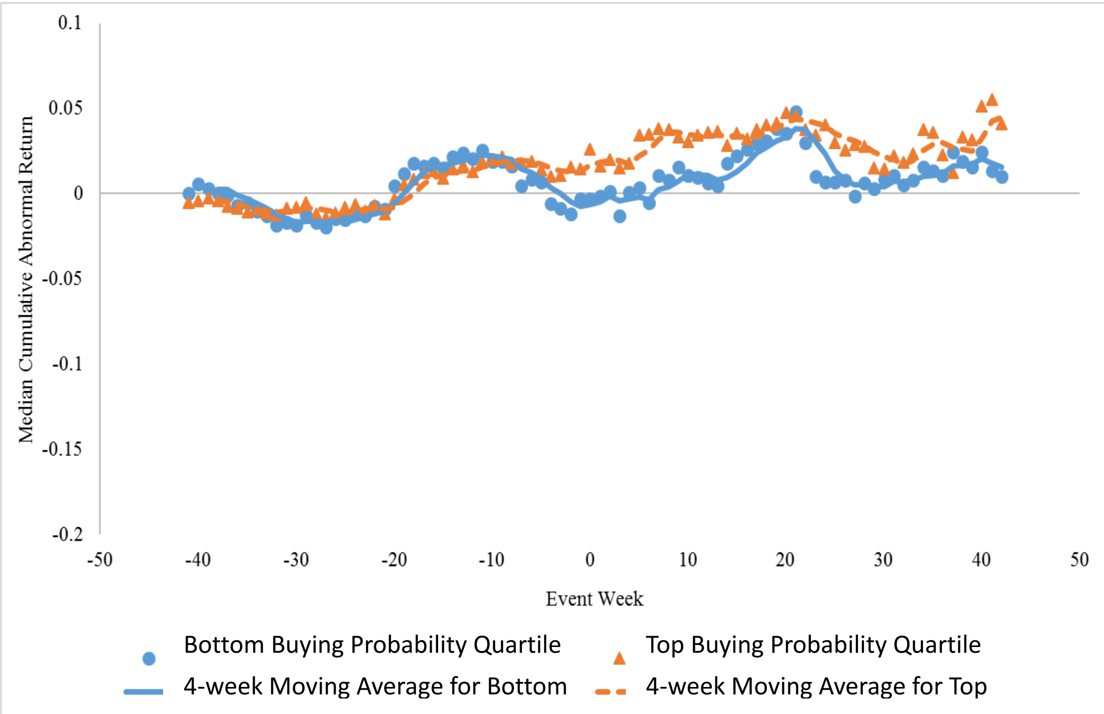


Figure 9: MACAR for Stocks sold by Different Investors. We take the sample in Figure 8 and partition the sample into two sub-samples according to the investor's identification of the other side of the transaction. Panel A presents the MCAR for those stocks that are sold by affected insurers. Panel B presents the MCAR for those stocks sold by all other investors. For each sample, similar to Figure 8, I present the MCAR for top and bottom buying probability quartiles. The probability estimation and the MCAR calculation are the same as those used in Figure 8.

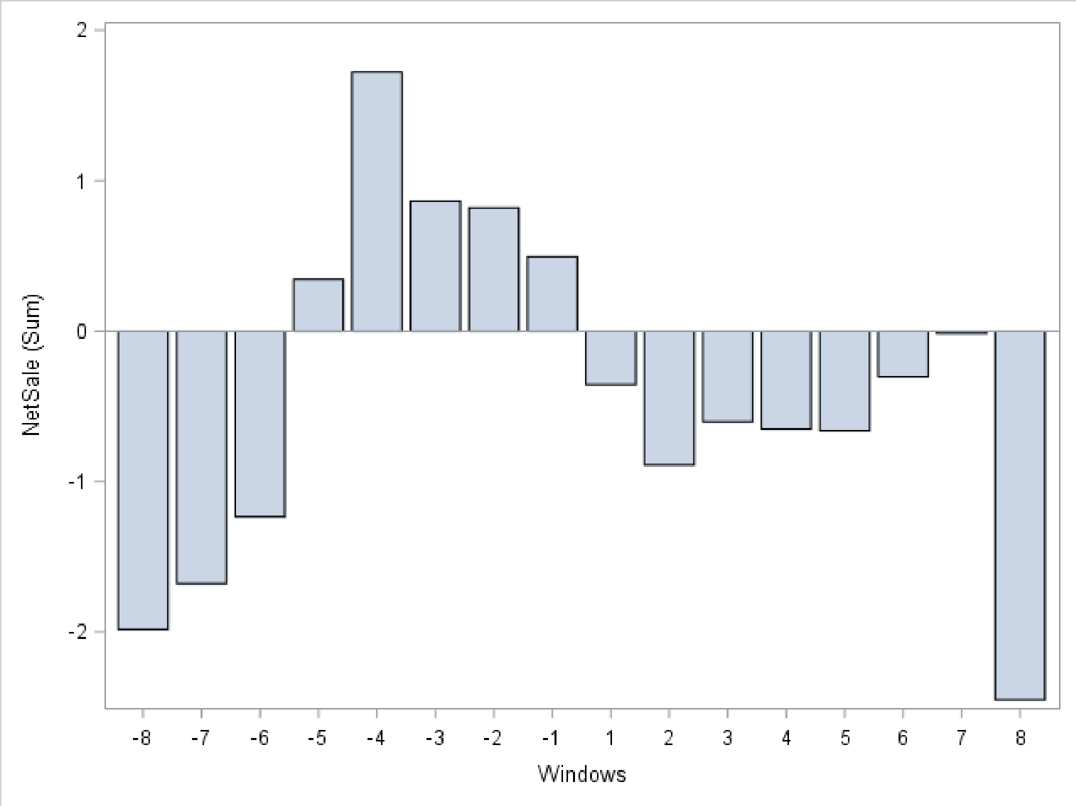


Figure 10: Net sales of the Bonds for Life Insurers. I keep those bonds net purchased by unaffected insurers during a [-45,+45] event-week period and I use Mergent FISD to identify life insurers who also trade the same bonds during the same period. Due to data limitation, I can only calculate the net sales of these bonds by life insurers on quarterly basis from t=-8 to t=+8 event-quarter. Quarterly net sale of a given bond is computed as total quarterly sales subtracted by total quarterly purchases.

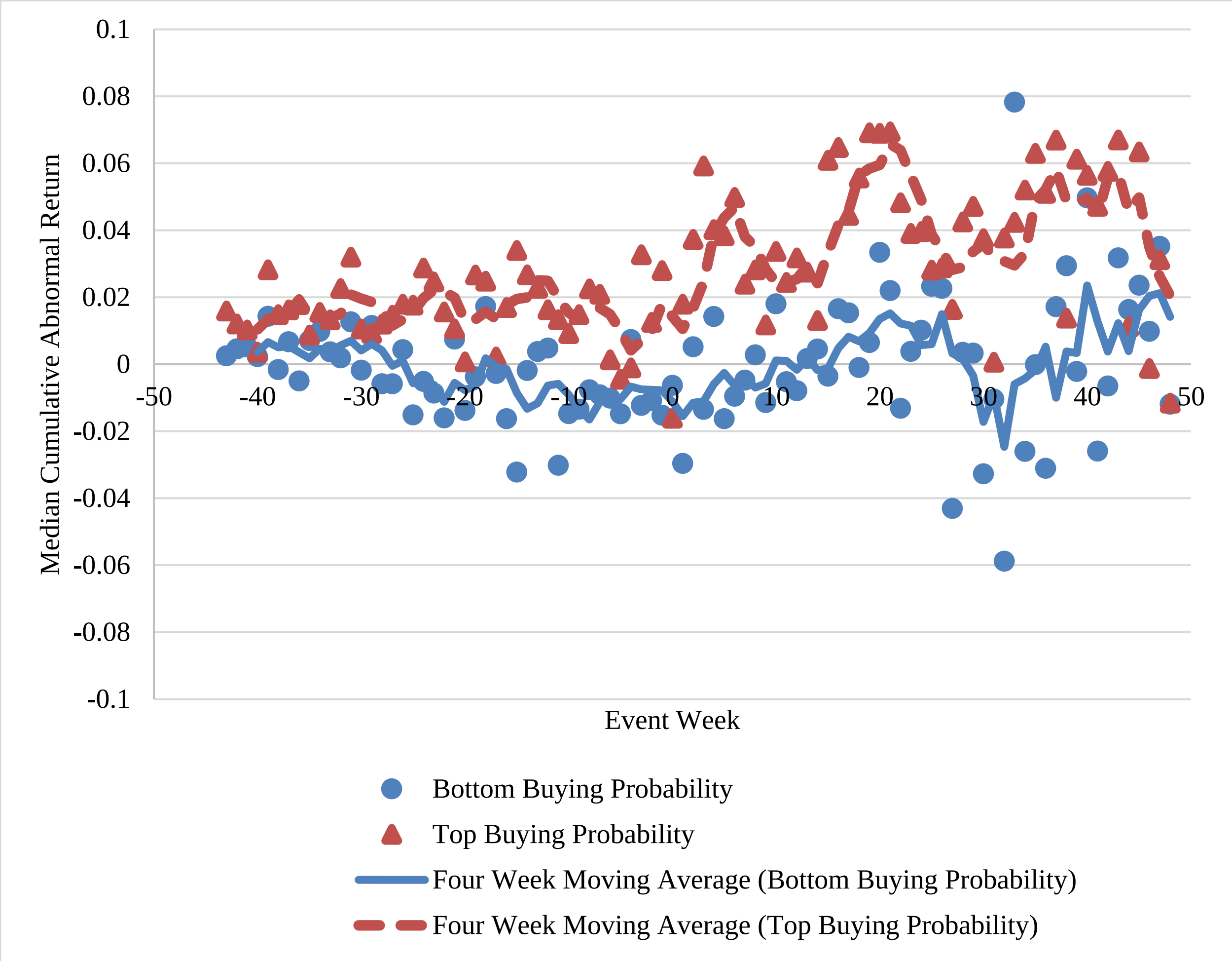


Figure 11: Bond MCAR around Hurricane Flossie. To address survivorship bias, I examine announced hurricane that did not make landfill. Flossie originated from a tropical wave that emerged off Africa on July 21, 2007. After traversing the tropical Atlantic, the wave crossed Central America and entered the eastern Pacific on August 1. There, a favorable environment allowed it to become a tropical depression and a tropical storm shortly thereafter on August 8. On August 11, Flossie became a major hurricane, but quickly deteriorated to a tropical depression by August 16, 2007. I define August 8 as the event day 0, and repeat the above Hurricane Katrina analysis for Hurricane Flossie. The MCAR and probability estimation are exactly the same as those in Figure 5. In the case of Hurricane Flossie, the state most likely to be affected is the state of Hawaii. However, there are few insurers located in Hawaii, leading to inadequate observations for most regression analysis. I assume all insurers except for Hawaii insurers are unaffected insurers and run the probit model used in Figure 5. Bonds are then assigned into top quartile and bottom quartile buying probability groups.

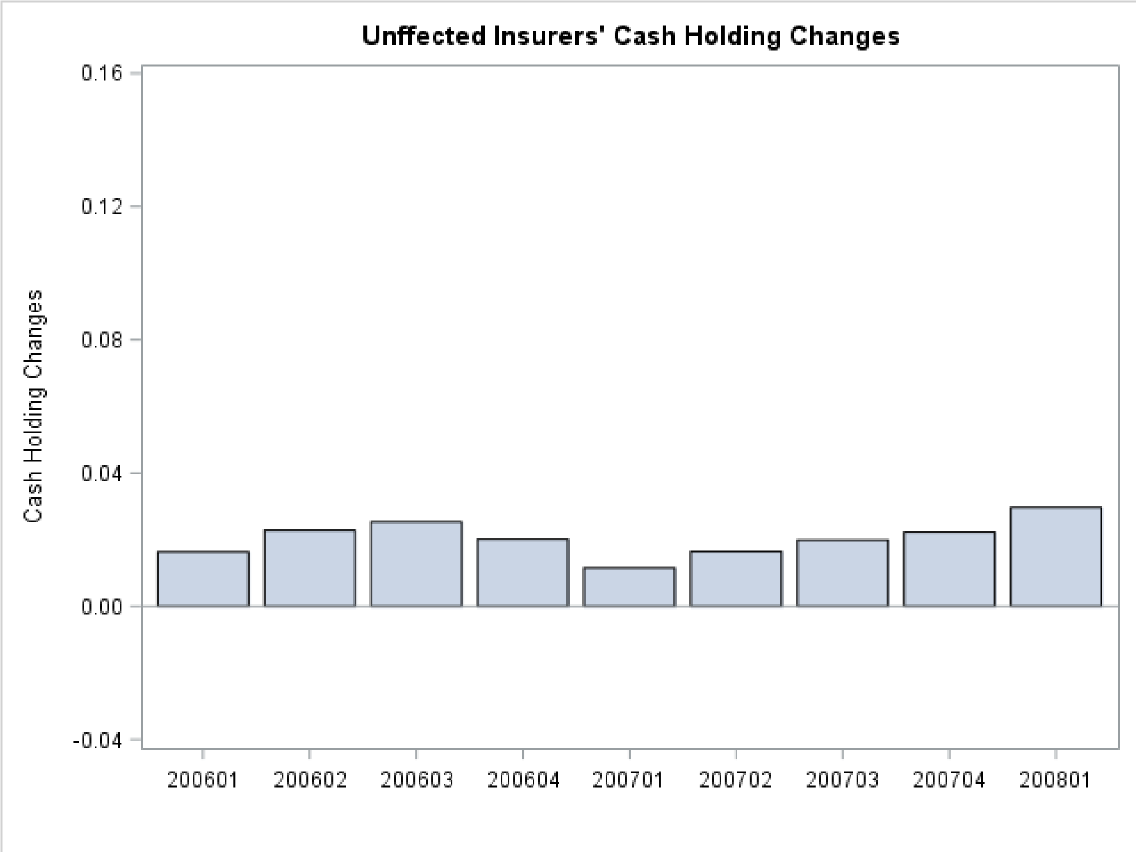


Figure 12: Cash Holding Changes of Insurers around Hurricane Flossie. I plot the cash holding changes for unaffected insurers around Hurricane Flossie. Change in cash holdings is computed as the difference between quarter *t* and quarter *t-1* cash balance scaled by total invested assets at quarter *t-1*. I assume all insurers except for Hawaii insurers are unaffected insurers

Table 1: Summary Statistics

Panel A reports holding-level characteristics, insurer characteristics and other variables used in the regression models. Panel B report security-level information. *Cash, Bond, and Stock Holdings* are cash, bond, stock positions at quarter-end scaled by total invested assets at the previous quarter end. *Insurer size* is natural log value of total invested asset. *Group* is a dummy variable if an insurer belongs to an insurance group, and zero otherwise. *Non-invested asset holding* is the non-invested asset position scaled by total invested assets at the previous quarter end. *Leverage* is the ratio of total liability to total assets. *Asset growth* proxies for investment opportunities for insurers according to Colquitt et al (1999). It is estimated as the average growth in total assets over the previous three years. *Cash Flow Std* is a proxy for volatility of insurer cash flow and is calculated as the standard deviation of total operating cash flow over the previous three years. *Duration* proxies for duration of insurers' liabilities, and is estimated as the weighted average of durations reported for insurance lines, with the weights being based on each insurer's unpaid losses. *Insurers' rating* is the rating of insurers provided by A.M.Best. *Issue size* is log value of total offering amount. *Bond age* is log value of the age of a given bond. *Bond Rating* is a single numerical rating for each bond according to the lowest rating assigned by three rating agencies. *Spread* is a matched treasury yield spread. Panel C reports the summary statistics for affected and unaffected insurers. Panel D reports the summary statistics for pre-Katrina and post-Katrina periods. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Holding-level

Variable	N	Mean	Median	P25	P75	Std
Cash Holding	52680	0.18	0.10	0.04	0.23	0.22
Bond Holding	52680	0.70	0.76	0.58	0.89	0.25
Stock Holding	52680	0.11	0.03	0.00	0.15	0.16
Insurer Size	52678	17.74	17.55	16.37	18.96	1.91
Group	52680	0.71	1.00	0.00	1.00	0.45
Non-invested Asset Holding	52679	0.18	0.14	0.06	0.23	0.17
Leverage	52679	0.51	0.58	0.34	0.7	0.26
Asset Growth	52675	0.01	0.01	-0.01	0.04	0.16
Cash Flow Std	52413	0.02	0.00	0.00	0.01	0.1
Duration	52680	1.99	1.83	1.63	2.08	0.76
Insurers' Rating	52680	5.47	4.00	3.00	5.00	4.77

Panel B: Security-level

Variable	N	Mean	Median	P25	P75	Std
Issue Size	85883	13.39	13.3	12.77	13.82	0.82
Bond Age	85883	0.48	0.74	0.10	1.41	1.43
Bond Rating	85867	7.51	7.00	5.00	9.00	3.50
Spread	83530	7.14	1.34	0.71	2.54	258.44

Panel C: Unaffected v.s. Affected

Variable	Unaffected			Affected			Difference	
	N	Mean	Std	N	Mean	Std	(1)-(2)	t-statistics
Insurer Size	50834	17.70	1.89	1844	18.89	2.22	-1.19***	(-26.47)
Cash Holding	50836	0.18	0.22	1844	0.10	0.17	0.08***	(15.78)
Stock Holding	50836	0.11	0.16	1844	0.08	0.15	0.03***	(6.61)
Bond Holding	50836	0.69	0.25	1844	0.79	0.24	-0.10***	(-16.68)
Group	50836	0.70	0.46	1844	0.98	0.15	-0.28***	(-25.65)
Non-invested Holding	50835	0.17	0.16	1844	0.27	0.22	-0.10***	(-23.34)
Leverage	50835	0.51	0.26	1844	0.55	0.27	-0.04***	(-6.35)
Asset Growth	50831	0.01	0.15	1844	0.02	0.25	-0.01	(-1.54)
Cash Flow Std	50574	0.02	0.09	1839	0.08	0.24	-0.06***	(-25.28)
Duration	50836	2.00	0.77	1844	1.73	0.48	0.27***	(14.69)
Insurers' Rating	50836	5.56	4.79	1844	3.04	3.32	2.52***	(22.36)
Issue Size	82346	13.38	0.82	3537	13.44	0.82	-0.06***	(-4.06)
Bond Age	82346	0.48	1.43	3537	0.32	1.46	0.16***	(6.42)
Bond Rating	82331	7.48	3.48	3536	8.18	3.78	-0.70***	(-11.65)
Spread	80156	7.29	263.79	3374	3.67	20.02	3.62	(0.79)

Panel D: Pre-Katrina v.s. Post Katrina

Variable	Post-Katrina			Pre-Katrina			Difference	
	N	Mean	Std	N	Mean	Std	(1)-(2)	t-statistics
Insurer Size	22645	17.79	1.96	30033	17.70	1.88	0.09***	(5.42)
Cash Holding	22646	0.19	0.23	30034	0.18	0.21	0.01***	(6.33)
Stock Holding	22646	0.10	0.16	30034	0.11	0.16	-0.01***	(-2.74)
Bond Holding	22646	0.69	0.26	30034	0.70	0.24	-0.01***	(-4.27)
Group	22646	0.69	0.46	30034	0.73	0.44	-0.04***	(-10.14)
Non-invested Holding	22646	0.18	0.17	30033	0.18	0.16	0.00***	(-2.67)
Leverage	22646	0.50	0.26	30033	0.51	0.27	-0.01***	(-4.66)
Asset Growth	22645	0.01	0.14	30030	0.02	0.17	-0.01***	(-7.93)
Cash Flow Std	22540	0.02	0.11	29873	0.02	0.09	0.00**	(2.35)
Duration	22646	2.05	0.85	30034	1.94	0.69	0.11***	(15.74)
Insurers' Rating	22646	5.93	5.21	30034	5.12	4.37	0.81***	(19.45)
Issue Size	30123	13.45	0.81	55760	13.35	0.83	0.10***	(16.39)
Bond Age	30123	0.45	1.53	55760	0.49	1.37	-0.04***	(-3.26)
Bond Rating	30121	7.66	3.64	55746	7.43	3.42	0.23***	(9.46)
Spread	29391	14.69	433.58	54139	3.04	30.80	11.65***	(6.22)

Table 2: Univariate Analysis

Panel A, Panel B, and Panel C report univariate analysis for cash holding, bond holding and stock holding, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Cash Holding

	Pre-Katrina			Post-Katrina			Differences	
	N	Mean	Std	N	Mean	Std	Mean	t-statistic
Unaffected	28956	0.18	0.21	21880	0.19	0.23	0.01	(5.59)
Affected	1078	0.09	0.16	766	0.13	0.19	0.04	(4.95)
Differences	0.09 (14.41)***			0.06 (7.64)***			-0.03 (-2.97)***	

Panel B: Bond Holding

	Pre-Katrina			Post-Katrina			Differences	
	N	Mean	Std	N	Mean	Std	Mean	t-statistic
Unaffected	28956	0.70	0.24	21880	0.69	0.26	-0.01	(3.77)
Affected	1078	0.80	0.23	766	0.77	0.24	-0.03	(2.55)
Differences	-0.10 (-14.24)***			-0.08 (-9.11)***			0.02 (1.69)*	

Panel C: Stock Holding

	Pre-Katrina			Post-Katrina			Differences	
	N	Mean	Std	N	Mean	Std	Mean	t-statistic
Unaffected	28956	0.11	0.16	21880	0.10	0.16	-0.01	(2.66)
Affected	1078	0.08	0.15	766	0.08	0.15	0.00	(0.90)
Differences	0.3 (4.85)***			0.02 (4.52)***			-0.01 (0.72)	

Table 3: Difference-in-differences estimation (propensity score matching)

This table reports the results from difference-in-differences estimation using propensity score matching. I match each treatment observation with a control observation that has exactly the same group, rating, and time variable. In addition, I use propensity score matching on other insurer characteristics (including *CFStd, Duration, Size, Non-invested Asset Holding, Group, Leverage*) to obtain the nearest-neighbor matches. Matching is done with no replacement and a caliper of 1%. However, the results hold if I require matching with replacement or if I do not impose a caliper. *CFStd* is the standard deviation of past 3-year operating cash flow. *Duration* proxies for duration of insurers' liabilities, and is estimated as the weighted average of durations reported for insurance lines, with the weights being based on each insurer's unpaid losses. *Non-invested Asset Holding* is the non-invested asset at quarter *t* divided by total invested assets at quarter *t-1*. Majority of the non-invested assets are real-estate properties. *Group* is a dummy variable that equals 1 if an insurer belongs to an insurance group, and zero otherwise. *Leverage* is total liability divided by total asset. Panel A of reports the logit regression results for the propensity score matching. Panel B compare the pre-Katrina differences in various characteristics. Panel C perform the difference-in-differences analysis on the match sample. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Logit regression in propensity score matching (Unaffected=1)

	(1) Original Sample before Hurricane Katrina	(1) Matched Sample before Hurricane Katrina
CFStd	-0.1356	-0.1846
	(-0.65)	(-0.79)
Duration	0.7194***	0.0844
	(7.37)	(0.86)
Size	-0.5573***	0.0199
	(-18.25)	(0.59)
Non-invested Asset Holding	-4.6424***	0.3158
	(-17.59)	(1.09)
Group	-2.1860***	0.0607
	(-7.95)	(0.20)
Leverage	2.3023***	-0.1092
	(9.95)	(-0.42)
Intercept	13.7549***	-0.6472
	(23.44)	(-1.07)
N	22539	2142

Panel B: Pre-Katrina differences

	Unaffected Insurers				Affected Insurers				Differences	
Variables	N	Mean	Median	Std	N	Mean	Median	Std	Mean	t-statistic
Exact Matching										
Year-Quarter										
Group										
Insurer Rating										
Propensity Score Matching										
CFStd	1071	0.07	0.01	0.22	1071	0.07	0.01	0.23	0.00	0.06
Duration	1071	1.74	1.76	0.43	1071	1.72	1.63	0.49	0.02	1.03
Rating	1071	0.08	0.00	0.27	1071	0.08	0.00	0.26	0.00	0.32
Size	1071	18.84	18.69	2.29	1071	18.77	18.41	2.21	0.07	0.72
Non-invested Asset Holding	1071	0.27	0.21	0.22	1071	0.27	0.21	0.23	0.00	0.60
Leverage	1071	0.55	0.64	0.25	1071	0.55	0.65	0.27	0.00	0.34
Stockholding	1071	0.09	0.03	0.13	1071	0.08	0.00	0.15	0.01	1.69
Parallel Trend Tests										
Cash Holding Changes	1071	0.00	0.00	0.05	1071	0.00	0.00	0.03	0.00	-0.87
Bond Holding Changes	1071	0.03	0.01	0.13	1071	0.04	0.01	0.90	-0.01	-1.17
Stock Holding Changes	1070	0.00	0.00	0.21	1068	-0.01	0.00	0.14	0.00	0.42

Panel C: Difference-in-differences (DiD) estimators

	N	Mean Unaffected Insurers' Differences (after-before)	Mean Affected Insurers' Differences (after-before)	Mean DiDs (Unaffected-Affected)
Cash Holding	2142	-0.0228**	0.0394***	-0.0622***
		(-2.58)	(4.14)	(-4.78)
Bond Holding	2142	0.0360**	-0.0263*	0.0633**
		(2.56)	(-1.87)	(2.20)
Stock Holding	2142	0.0046	-0.0018	0.0064
		(0.45)	(-0.20)	(0.47)

Table 4: Difference-in-differences estimation (fixed effect panel regressions)

This table reports the results from difference-in-differences estimation using fixed-effect panel regressions. *Unaffected* equals one for unaffected insurers and zero otherwise. *PostKatrina* equals one for period after 200502 and zero otherwise. All other control variables are defined exactly the same as those in Table 3. Standard errors are clustered at insurer-level. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Cash	(2) Bonds	(3) Stocks	(4) Cash	(5) Bonds	(6) Stocks
Unaffected	0.0629***	-0.0420**	-0.0155	0.0634***	-0.0440**	-0.0151
	(3.12)	(-2.14)	(-1.64)	(3.36)	(-2.28)	(-1.62)
PostKatrina	0.0395***	-0.0371***	-0.0024	0.0640***	-0.0495***	-0.0077
	(3.82)	(-3.03)	(-0.34)	(6.29)	(-4.00)	(-1.12)
Unaffected	-0.0480***	0.0446***	0.0005	-0.0527***	0.0462***	0.0001
*PostKatrina	(-4.72)	(3.74)	(0.07)	(-5.28)	(3.82)	(0.01)
AssetGrowth				0.2612***	-0.0493***	-0.0028
				(14.34)	(-5.42)	(-0.83)
CFStd				0.0304**	-0.0240	-0.0007
				(2.36)	(-1.60)	(-0.05)
Duration				0.0073	-0.0010	-0.0048*
				(1.37)	(-0.19)	(-1.76)
Rating				0.0020*	-0.0025*	0.0003
				(1.69)	(-1.96)	(0.38)
Insurer Size				-0.0586***	0.0374***	0.0208***
				(-10.18)	(6.27)	(5.71)
Non-invested				-0.0775***	0.0235	0.0401***
Asset Holding				(-3.51)	(1.07)	(3.53)
Leverage				0.1197***	-0.0662***	-0.0537***
				(5.84)	(-4.11)	(-4.27)
Intercept	0.1207***	0.7354***	0.1221***	1.0879***	0.1238	-0.2294***
	(5.91)	(37.08)	(12.72)	(10.75)	(1.17)	(-3.59)
Observations	52,680	52,680	52,680	52,408	52,408	52,408
Insurer FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Cluster by Insurer	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.003	0.002	0.001	0.111	0.017	0.018

Table 5: Difference-in-difference estimation for bond holding by pre-Katrina cash quartiles

This table reports the results from difference-in-differences estimation using fixed-effect panel regressions by pre-Katrina cash holding quartiles. I take the full sample and sort it into quartiles according to pre-Katrina cash holdings or pre-Katrina abnormal cash holdings. To estimate abnormal cash holding, I run model 4 of Table 4 using only unaffected insurers during the sample before 2005Q2 (e.g. *Unaffected, PostKatrina, and Unaffected*PostKatrina* are dropped out). I estimate abnormal change in cash holdings for a given insurer as the residual from the cross-sectional regression. All explanatory variables are measured contemporaneously with or before the time when cash holdings are observed, and consequently the estimation introduces no look-ahead bias. Panel A presents the results for raw cash holding quartiles. Panel B presents the results for abnormal cash holding quartiles. Standard errors are clustered at insurer-level. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Raw cash holding quartiles

	N	Mean Differences in Bond Holdings for Unaffected Insurers (after-before)	Mean Differences in Bond Holdings for Affected Insurers (after-before)	Mean DiDs (Unaffected-Affected)
Bottom	13102	-0.0199**	-0.0375*	0.0175
		(-5.19)	(-2.38)	(1.08)
Quartile 2	13102	0.0041	-0.0296	0.0338
		(0.36)	(-1.37)	(1.38)
Quartile 3	13102	-0.0039	-0.0089	0.0050
		(-0.94)	(-1.00)	(0.51)
Top	13102	0.0504***	0.0208*	0.0296**
		(5.23)	(1.98)	(2.69)

Panel B: Abnormal cash holding quartiles

	N	Mean Differences in Bond Holdings for Unaffected Insurers (after-before)	Mean Differences in Bond Holdings for Affected Insurers (after-before)	Mean DiDs (Unaffected-Affected)
Bottom	13102	-0.0400***	-0.0164*	-0.0236**
		(-8.09)	(-1.96)	(-2.11)
Quartile 2	13102	-0.0079**	-0.0156	0.0077
		(-2.69)	(-1.39)	(0.66)
Quartile 3	13102	-0.0055**	0.0012	-0.0067
		(-2.43)	(0.09)	(-0.49)
Top	13102	0.0478**	0.0142	0.0338**
		(8.65)	(1.19)	(2.58)

Table 6: Placebo Tests.

I re-run the difference-in-difference tests using fixed-effect panel regressions in Table 5 but with different event time. This table then reports the coefficient estimates only for the difference-in-difference term. Standard errors are clustered at insurer-level. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Cash Holding	Bond Holding	Stock Holding
Unaffected*PostKatrina (=2006Q4)	0.0115	-0.0128	0.0059
	(0.89)	(-0.88)	(0.62)
Unaffected*PostKatrina (=2006Q3)	0.0056	-0.0039	0.0033
	(0.48)	(-0.29)	(0.40)
Unaffected*PostKatrina (=2006Q2)	-0.0067	0.0052	0.0029
	(-0.60)	(0.41)	(0.39)
Unaffected*PostKatrina (=2006Q1)	-0.0075	0.0092	0.0144
	(-0.49)	(0.66)	(1.49)
Unaffected*PostKatrina (=2004Q4)	-0.0097	0.0149	-0.0013
	(-0.93)	(1.36)	(-0.23)
Unaffected*PostKatrina (=2004Q3)	-0.0088	0.0174*	-0.0014
	(-0.85)	(1.77)	(-0.32)
Unaffected*PostKatrina (=2004Q2)	-0.0050	0.0150	-0.0006
	(-0.54)	(1.29)	(-0.16)
Unaffected*PostKatrina (=2004Q1)	0.0001	0.0074	0.0010
	(0.01)	(0.92)	(0.26)
Unaffected*PostKatrina (=2003Q4)	0.0013	0.0040	0.0007
	(0.16)	(0.46)	(0.17)
Unaffected*PostKatrina (=2003Q3)	0.0031	0.0021	0.0005
	(0.37)	(0.24)	(0.13)
Unaffected*PostKatrina (=2003Q2)	0.0010	-0.0054	0.0007
	(1.27)	(-0.62)	(0.15)
Unaffected*PostKatrina (=2003Q1)	-0.0015	0.0097	0.0007
	(-0.16)	(0.87)	(0.14)
Unaffected*PostKatrina (=2002Q4)	0.0029	0.0013	0.0014
	(0.29)	(0.11)	(0.26)
Unaffected*PostKatrina (=2002Q3)	0.0054	-0.0046	0.0020
	(0.49)	(-0.34)	(0.31)
Unaffected*PostKatrina (=2002Q2)	0.0068	-0.0153	0.0047
	(0.46)	(-1.010	(0.48)
Insurer FE	YES	YES	YES
Quarter FE	YES	YES	YES
Cluster by Insurer	YES	YES	YES

Table 7: Probability of buying bonds around Hurricane Katrina.

I model the probability that an insurer will buy bonds during quarters 0 to +2 after Hurricane Katrina as a probit regression where the dependent variable equals 1 if an insurer purchase bonds during two quarters after Hurricane Katrina, zero otherwise. *Prior Cash* is simply the cash holding at 2005Q2. *Unaffected* equals one for unaffected insurers and zero otherwise. All control variables are defined as those in Table 1. Panel A reports the results for all sample bonds. Panel B reports results for sub-sample bonds that are sold and purchased back by unaffected insurers. Panel C further require bonds to be sole and purchased back by the same unaffected insurers. Standard errors are clustered at bond-level. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: All Bonds

	Buying during quarters 0 to +2			Buying during quarters -2 to 0		
	(1)	(2)	(3)	(4)	(5)	(6)
	Unaffected	Affected	Unaffected v.s. Affected	Unaffected	Affected	Unaffected v.s. Affected
Prior Cash	0.9884***	0.2167	-3.3845**	-0.6504***	-0.4174***	0.2195***
	(4.38)	(1.24)	(-2.39)	(-13.33)	(6.59)	(3.05)
Unaffected			0.2167			-0.0308
			(1.51)			(1.32)
Unaffected *Prior Cash			4.3655***			-0.8549***
			(3.06)			(-9.99)
Insurer Size	0.0901***	0.5440***	0.0876***	-0.0876***	-0.0863**	-0.0809***
	(4.35)	(3.88)	(4.27)	(-21.40)	(-2.10)	(-20.38)
Non-invested Asset Holding	-1.1544***	-1.5765***	-1.1273***	0.4170***	3.1315***	0.3829***
	(-4.51)	(4.43)	(-4.49)	(9.68)	(-6.89)	(8.94)
Leverage	-0.5237***	-0.0544	-0.5053***	0.5025***	0.9514***	0.5030***
	(-3.16)	(-0.21)	(-3.09)	(17.72)	(5.22)	(18.17)
CFStd	-0.3809***	-0.9284***	-0.3556***	0.1560***	0.3268***	0.0497***
	(-2.67)	(-3.61)	(-3.62)	(7.03)	(-5.14)	(2.77)
Issue Size	0.0656***	0.1067***	0.0675***	-0.1238***	-0.0197	-0.1214***
	(5.23)	(2.87)	(5.52)	(-8.90)	(-0.73)	(-8.83)
Bond Age	-0.1080***	-0.0275	-0.1054***	-0.0771***	-0.0536***	-0.0750***
	(-12.00)	(-1.38)	(-11.88)	(-9.90)	(-3.62)	(-9.78)
Bond Rating	-0.0116**	-0.0047	-0.0107**	-0.0313***	0.0118*	-0.0298***
	(-2.26)	(-0.53)	(-2.11)	(-11.10)	(1.91)	(-10.69)
Intercept	-3.0032***	-7.2921***	-2.7883***	2.8666***	1.8362*	2.6755***
	(-7.24)	(-4.58)	(-6.22)	(13.88)	(1.85)	(13.05)
Observations	82292	3536	85828	82292	3536	85828
Pseudo R^2	0.038	0.037	0.037	0.026	0.059	0.026
Log likelihood	-36476	-1254	-37775	-51238	-2026	-53373

Panel B: Same Bonds sold before Katrina by Unaffected Insurers

Prior Cash	0.9132***	-5.4113***	-3.7832***	-0.3426***	2.1036***	2.3923***
	(11.71)	(-4.23)	(-6.77)	(-6.68)	(3.40)	(7.69)
Unaffected			-0.2478***			0.2222***
			(-3.66)			(5.22)
Unaffected *Prior Cash			4.6811***			-2.7320***
			(8.27)			(-8.70)
Insurer Controls	YES	YES	YES	YES	YES	YES
Bond Controls	YES	YES	YES	YES	YES	YES
Intercept	-4.1582***	-10.0418**	-3.8526***	2.3572***	0.2260	2.1185***
	(-13.29)	(-2.34)	(-12.45)	(12.23)	(0.14)	(11.26)
Observations	65939	2693	68632	65939	2693	68632
Pseudo R^2	0.070	0.103	0.070	0.053	0.039	0.052
Log likelihood	-19813	-642	-20471	-41726	-1691	-43441

Panel C: Same Bonds sold Pre-Katrina by the Same Unaffected Insurers

Prior Cash	1.1889***	-10.9729***	-6.5491***	0.0967	0.9994**	0.4168
	(3.98)	(-2.92)	(-6.27)	(1.53)	(1.96)	(1.34)
Unaffected			-0.8641***			-0.0823*
			(-9.12)			(-1.94)
Unaffected *Prior Cash			7.6594***			-0.3228
			(7.06)			(-1.02)
Insurer Controls	YES	YES	YES	YES	YES	YES
Bond Controls	YES	YES	YES	YES	YES	YES
Intercept	-10.8257***	-32.9283**	-9.5178***	-1.4979***	-2.1241	-1.3357***
	(-15.92)	(-2.42)	(-15.38)	(-7.59)	(-1.53)	(-6.95)
Observations	36684	1971	38655	36684	1971	38655
Pseudo R^2	0.126	0.182	0.128	0.022	0.020	0.021
Log likelihood	-2566	-219	-2803	-21160	-1194	-22363

Table 8: MCAR by average buying probability

This table reports the median cumulative abnormal returns for bonds grouped by the average buying probability during 2 quarters after hurricane Katrina. To measure bond returns, I first use tick-by-tick transaction data from TRACE to compute volume-weight daily bond prices and supplement the "clean" prices with accrued interests (accrued interests are from FISD matching on bond CUSIPs). I then calculate weekly bond returns as the change in the "dirty" prices from the end of a week to the end of the next week, adding in any coupons paid during the week. To estimate abnormal bond returns, I use a simple mean-adjusted model in which an excess holding period return and an expected excess return need to be estimated first. I use week [-80,-50) as the estimation window to calculate mean excess returns and use week [-45,+45] as the event window to estimate cumulative abnormal bond returns (CAR). I calculate the median cumulative abnormal return, *MCAR,* as the median of the CARs across all bonds in a particular group that trade in each event week. I model the probability that an insurer will buy bonds during quarters 0 to +2 after Hurricane Katrina as a probit function where the dependent variable is a dummy variable that equals one if an insurer buys bond during quarter [0,+2] and zero otherwise. The independent variables include several insurer characteristics and bond characteristics. According to the estimated bond-level average buying probability, I then sort bonds into quartiles, and present the results for the top quartile and bottom quartile bonds. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Top Buying Probability		Bottom Buying Probability		Difference	
	MCAR (1)	t-statistics	MCAR (2)	t-statistics	(1)-(2)	t-statistics
[-40,-31]	0.10	(0.47)	0.88	(4.19)	-0.79	(-2.42)
[-30,-21]	-5.60	(-12.79)	-1.02	(-3.36)	-4.58	(-8.37)
[-20,-11]	-8.99	(-11.56)	-2.89	(-8.45)	-6.10	(-6.97)
[-10,-1]	-8.99	(-8.81)	-2.76	(-5.55)	-6.23	(-5.42)
Week 0	-11.24	(-2.94)	0.09	(0.04)	-11.33	(-2.49)
[1,10]	-6.94	(-5.18)	-2.88	(-2.98)	-4.06	(-2.46)
[11,20]	-5.04	(-4.54)	-0.34	(-0.30)	-4.70	(-2.81)
[21,30]	-1.62	(-4.51)	-4.79	(-1.78)	3.17	(1.91)
[31,40]	-1.08	(-2.00)	-5.11	(-1.53)	4.03	(1.86)

Table 9: Probability of Buying Bonds issued by Affected Issuers around Katrina.

This table repeat Table 7 on a different sample of bonds issued by affected issuers. We define a bond issuer is affected if the issuer's headquarter is in one of the states of Alabama, Mississippi, Louisiana or if the issuer is in industries that are related to natural oil, gas, petroleum, or airlines. I identify 5000 observations and 4700 observations are transactions by unaffected insurers, while 300 observations are for affected insurers. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Buying during quarters 0 to +2			Buying during quarters -2 to 0		
	(1)	(2)	(3)	(4)	(5)	(6)
	Unaffected	Affected	Unaffected v.s. Affected	Unaffected	Affected	Unaffected v.s. Affected
Prior Cash	0.6510**	-3.4330	-5.5608***	-0.7502***	10.5736***	6.2327***
	(2.56)	(-0.80)	(-3.05)	(-3.31)	(3.71)	(5.75)
Unaffected			-0.3690**			0.7608***
			(-1.98)			(4.88)
Unaffected *Prior Cash			6.1961***			-6.9826***
			(3.36)			(-6.31)
Insurer Size	0.1288***	0.2066	0.1202***	-0.0750***	-0.4988	-0.0722***
	(6.76)	(0.41)	(6.71)	(-4.76)	(-1.64)	(-4.67)
Non-invested Asset Holding	-1.0903***	4.8081**	-1.0715***	0.2136	-0.9521	0.2506
	(-5.14)	(2.16)	(-5.10)	(1.35)	(-0.45)	(1.61)
Leverage	-0.8645***	-1.1192	-0.8411***	0.5485***	-1.3474*	0.5314***
	(-6.62)	(-1.06)	(-6.51)	(5.31)	(-1.74)	(5.21)
CFStd	-0.6241***	-0.0333	-0.5170***	0.4410***	1.1134*	0.3682***
	(-4.36)	(-0.03)	(-4.83)	(4.34)	(1.83)	(4.19)
Issue Size	0.0560	-0.1249	0.0507	-0.0964*	-0.0078	-0.0986*
	(1.11)	(-0.71)	(1.01)	(-1.71)	(-0.06)	(-1.76)
Bond Age	-0.1560***	0.0220	-0.1500***	-0.0475**	-0.1436**	-0.0518**
	(-5.19)	(0.31)	(-5.07)	(-2.03)	(-2.51)	(-2.26)
Bond Rating	-0.0252***	-0.0299	-0.0246***	-0.0367***	0.0561**	-0.0340***
	(-2.80)	(-0.92)	(-2.78)	(-4.82)	(2.56)	(-4.56)
Intercept	-3.2914***	-4.1104	-2.7182***	2.1901**	9.3849	1.3927*
	(-4.18)	(-0.35)	(-3.49)	(2.56)	(1.49)	(1.65)
Observations	6414	305	6719	6414	305	6719
Pseudo R^2	0.050	0.068	0.050	0.020	0.085	0.021
Log likelihood	-2556	-85	-2649	-3802	-165	-3976

Table 10: Probability of Buying Stocks around Hurricane Katrina.

To compute stock abnormal returns, I first estimate expected stock returns using Carhart four-factor model in an estimation window of 200 trading days. I require there are at least 140 daily return available within the estimation window. I also require a 50-day gap between the estimation window and the event window of [-45,+45] event-week. I calculate the median cumulative abnormal return, *MCAR,* as the median of the CARs across all stocks in a particular group that trade in each event week. I model the probability that an insurer will buy stocks during quarters 0 to +2 after Hurricane Katrina as a probit function where the dependent variable is a dummy variable that equals one if an insurer buys bond during quarter [0,+2] and zero otherwise. The independent variables include several insurer characteristics and Carhart four factors. According to the estimated stock-level average buying probability, I then sort stock into quartiles. Finally, I present the MCAR for the top quartile and bottom quartile stocks. Standard errors are clustered at stock-level. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Buying during quarters 0 to +2			Buying during quarters -2 to 0		
	(1) Unaffected	(2) Affected	(3) (1) v.s. (2)	(4) Unaffected	(5) Affected	(6) (4) v.s. (5)
Prior Cash	0.0746	0.7330***	0.3594**	-0.0864*	-0.9188***	-0.3449*
	(0.72)	(3.82)	(2.00)	(-1.89)	(-4.41)	(-1.90)
Unaffected			0.0694***			0.1057***
			(3.35)			(8.44)
Unaffected*Prior Cash			-0.2212			0.2294
			(-1.13)			(1.23)
Insurer Size	-0.0151***	0.0444***	-0.0204***	0.0196***	-0.0057	0.0136***
	(-3.13)	(2.61)	(-4.41)	(6.34)	(-0.40)	(4.83)
Non-invested Asset	0.1542**	1.3216***	0.1133*	-0.4066***	1.2831***	-0.3103***
Holding	(2.18)	(3.67)	(1.66)	(-8.27)	(5.76)	(-6.56)
Leverage	0.1342***	-0.1903	0.1103**	-0.1332***	-0.2903***	-0.1682***
	(2.74)	(-1.31)	(2.34)	(-4.39)	(-2.77)	(-5.90)
CFStd	-0.0947***	0.0305	0.0593***	-0.0693***	0.0267	-0.0186
	(-5.23)	(1.03)	(4.24)	(-2.84)	(0.87)	(-1.29)
SMB	-4.7816*	-23.2953***	-8.3706***	-11.8454***	1.6172	-9.3284***
	(-1.86)	(-4.77)	(-3.53)	(-11.23)	(0.72)	(-9.78)
HML	7.2133	-10.8541	2.6457	-5.8488***	-7.8658**	-6.2922***
	(1.55)	(-1.13)	(0.60)	(-3.71)	(-2.32)	(-4.40)
Mkt-rf	-0.0982	-5.8471	-1.4011	4.9075***	-2.1871	3.6912***
	(-0.06)	(-1.52)	(-0.83)	(7.21)	(-1.50)	(5.99)
Rf	2.0690**	-3.7211	1.2272	-6.4400 ***	-7.3282**	-0.5907***
	(2.12)	(-1.49)	(1.17)	(-4.09)	(-2.13)	(-4.14)
UMD	-3.3414*	14.5799***	0.0359	8.0076***	12.3171***	8.7976***
	(-1.66)	(3.81)	(0.02)	(7.72)	(5.58)	(9.38)
Intercept	-0.0138	-0.6208	0.1393	-0.1476**	0.1928	-0.1301**
	(-0.08)	(-1.18)	(0.76)	(-2.36)	(0.72)	(-2.24)
Observations	43937	9176	53113	99787	21082	120869
R^2	0.002	0.011	0.002	0.003	0.004	0.003
Log likelihood	-30350	-6290	-36708	-68890	-14550	-83513

Table 11: Performance Analysis – Bond Portfolio Returns

Table 11 reports the results for the factor loadings and α. Using coupon rates from Mergent FISD and end-of-week volume-weighted transaction prices from TRACE, I calculate equal-weighted weekly returns on bonds acquired during the [-45, +45] event week period. Weekly bond returns are the change in the "dirty" prices from the end of a week to the end of the next week, adding in any coupons paid during the week. I choose the [-45,+45] event week period explicitly because, as my evidence suggests, this is likely to be the period one expect to witness significant bond fire sales. The risk-free rate and market returns are from Ken French's website. *Default premium* is the difference in returns between investment-grade and high-yield corporate bonds. *Term spread* is the difference in returns between the five-year Treasury bond and the three-month Treasury bill. Panel A provides results for all sample bonds in column (1), for bonds that are traded between insurers in column (2), and for bonds that are traded by non-insurers in column (3). Panel B provides results for bonds that are traded between insurers, for bonds net purchased by unaffected insurers in column (1) and (2), and for bonds net sold by unaffected insurers in column (4) and (5). *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Overview

	(1) All Bonds	(2) Bonds traded by Insurers	(3) Bonds traded by Non-insurers
Intercept ("α")	0.6503*	0.6387*	2.8194
	(1.86)	(1.83)	(1.07)
Stock Market Excess Return	0.0438*	0.0444*	0.0058
	(1.89)	(1.96)	(0.03)
Default Premium	0.2646**	0.2853**	-0.5646
	(2.15)	(2.33)	(-0.61)
Term Spread	0.0381***	0.0393***	0.0158
	(3.61)	(3.59)	(0.13)
Observations	90	90	90
R^2	0.148	0.161	0.005
Mean Excess Return	1.3421	1.3430	1.2121

Panel B: Bonds Traded between Insurers

	(1) Bonds Net Bought by Top Cash Unaffected Insurers	(2) Bonds Net Bought by Bottom Cash Unaffected Insurers	(3) Bonds Net Sold by Top Cash Unaffected Insurers	(4) Bonds Net Sold by Bottom Cash Unaffected Insurers
Intercept ("α")	0.8301**	0.5911*	0.4704	0.4654
	(2.46)	(1.73)	(0.77)	(0.88)
Stock Market Excess Return	0.0360	0.0346	0.0742**	0.0606*
	(1.35)	(1.50)	(2.01)	(1.82)
Default Premium	0.1400	0.2285*	0.3426	0.3452*
	(1.20)	(1.89)	(1.60)	(1.86)
Term Spread	0.0310**	0.0297**	0.0503***	0.0541***
	(2.14)	(2.47)	(4.33)	(5.19)
Observations	90	90	90	90
R^2	0.078	0.102	0.129	0.148
Mean Excess Return	1.1539	1.229	1.3885	1.3902

Table 12: Performance Analysis – Public Insurers' Stock Returns

This table reports stock α for publicly listed insurers. I examine the risk-adjusted returns for only public-listed unaffected insurers after controlling for the factor loadings using the capital asset pricing model, the Fama and French (1993) three-factor model, the Carhart et al (1997) four-factor model, and a five-factor model including Carhart et al (1997) model and the Pastor and Stambaugh (2003) liquidity factor. To assemble the stock price sample for public insurers, I use the Center for Research in Security Prices (CRSP) database to identify all publicly traded insurers during the [-45,+45] event-week period. Public insurers are firms with SIC codes of 6311 (life insurance), 6321 (accident and health insurance), 6324 (hospital and medical service plans), 6331 (fire, marine, and casualty insurance), 6351 (surety insurance), 6361 (title insurance), 6399 (insurance carriers), and 6411 (insurance agents, brokers, and services)}. This yields 659 insurers, including 244 life insurers. To identify affected insurers, unaffected insurers, unaffected insurers in top and bottom pre-Katrina cash quartiles, I manually match them to CRSP by names of the insurers. Out of the original sample of 84 affected insurers, I am able to match 80 of them. However, the matching for unaffected insurers are relatively less satisfactory. Out of the 412 insurers, I can only match 45 insurers for the top quartile and 24 insurers for the bottom quartile. t-statistics are reported in brackets beneath coefficient estimates. R^2 is reported beneath t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
	All Insurers	Affected Insurers	Unaffected Insurers	Unaffected Top Pre-Katrina Cash Quartile	Unaffected Bottom Pre-Katrina Cash Quartile
Market model alpha	0.0402	-1.1674	1.2479	1.2341	1.4525
	(0.03)	(-0.42)	(1.39)	(1.26)	(1.27)
	42.2	78.9	34.1	76.7	63.0
Fama-French three-factor alpha	-0.1309	-0.8672	0.6054**	0.5782**	0.7956*
	(-0.21)	(-0.71)	(2.74)	(2.17)	(1.86)
	46.3	78.8	45.7	76.8	62.8
Carhart four-factor alpha	-0.1460	-0.9029	0.6109**	0.5821**	0.8136*
	(-0.24)	(-0.75)	(2.68)	(2.15)	(1.87)
	46.6	78.9	46.8	76.8	64.0
Carhart & liquidity five-factor alpha	0.3542	-0.0878	0.7961**	0.8156**	0.6244
	(0.57)	(-0.07)	(2.63)	(2.35)	(1.72)
	51.5	80.5	55.1	79.2	66.0

Table 13: Life Insurers' Stock Performance

This table reports stock α for publicly listed life insurers. Life insurers are defined in CRSP as having SIC code of 6311. Column 1 is the capital asset pricing model. Column 2 presents the results for the Fama and French (1993) three-factor model. Column 3 presents the results for the Carhart et al (1997) four-factor model, and Column 4 presents the results for the five-factor model including Carhart et al (1997) model and the Pastor and Stambaugh (2003) liquidity factor. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)
Intercept ("α")	0.1083	1.6812***	1.6539***	1.6353***
	(0.08)	(3.71)	(3.66)	(3.01)
Risk-free	3.1556			
	(0.59)			
Market Excess Return	0.8839***	0.5218*	0.4956*	0.5075**
	(7.04)	(2.11)	(2.00)	(2.50)
SMB		0.2259	0.3259	0.3258
		(1.04)	(1.38)	(1.14)
HML		-0.6243*	-0.4985	-0.4662
		(-2.06)	(-1.53)	(-0.86)
MOM			-0.1988	-0.1850
			(-1.06)	(-0.74)
PSFactor				-0.0223
				(-0.10)
N	22	22	22	22
R^2	0.610	0.691	0.711	0.712

Table 14: Affected and Unaffected in the Same Insurance Group.

This table repeats the difference-in-differences fixed-effect panel regression analysis for a sub-sample of insurers. I require in this sub-sample affected and unaffected insurers are in the same insurance group. I control for insurer and quarter fixed effects. Standard errors are clustered at insurer-level. *t*-statistics are reported in brackets beneath coefficient estimates. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Cash	Bonds	Stocks	Cash	Bonds	Stocks
Unaffected	-0.0205	0.0679	-0.0432	-0.0098	0.0477	-0.0464
	(-0.32)	(0.90)	(-0.80)	(-0.16)	(0.59)	(-0.82)
PostKatrina	0.0828***	-0.0706**	-0.0243	0.0817***	-0.0700**	-0.0161
	(2.93)	(-2.19)	(-1.59)	(3.15)	(-2.28)	(-1.52)
Unaffected *PostKatrina	-0.0404	0.0347	0.0200	-0.0315	0.0302	0.0080
	(-1.42)	(1.07)	(1.25)	(-1.21)	(0.98)	(0.73)
AssetGrowth				0.2776***	-0.0970***	0.0015
				(12.38)	(-3.03)	(0.10)
CFStd				-0.0296	0.0478	-0.0386
				(-1.10)	(0.42)	(-0.51)
Duration				0.0509***	-0.0438**	-0.0105
				(2.80)	(-2.10)	(-1.14)
Rating				0.0083***	-0.0051	-0.0024*
				(2.92)	(-1.58)	(-1.97)
Size				-0.0367*	0.0245	0.0255
				(-1.92)	(0.72)	(1.08)
Non-invested				0.0331	-0.1481**	0.1156***
				(0.54)	(-1.99)	(3.67)
Group				0.0044	-0.0698	0.0761***
				(0.10)	(-1.53)	(2.66)
Leverage				0.0824*	-0.0210	-0.0771***
				(1.87)	(-0.39)	(-3.12)
Intercept	0.1451**	0.6882***	0.1411***	0.6380*	0.4611	-0.3616
	(2.43)	(9.79)	(2.86)	(1.75)	(0.74)	(-0.85)
Observations	3422	3422	3422	3421	3421	3421
Insurer FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Cluster by Insurer	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.034	0.023	0.005	0.149	0.060	0.046