# Putting Everything under the Same Umbrella – Hazard-Specific Supply Reactions in the Aftermath of Natural Disasters

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**Abstract**

Prior studies on the impact of catastrophes on insurance markets have either focused on one specific type of hazard or pooled several natural disasters. In contrast, we analyze insurers' hazard-specific supply reactions. We analyze U.S. property insurers' supply decisions between 1991-2012 and find that insurers' responses with respect to reduction of business volume and exit decisions differ across hazards, even after controlling for the damage size. The negative effects of catastrophes on underwriting performance and subsequent supply decisions are more pronounced for hurricanes than for the other hazards. We argue that supply distortions in the aftermath of unprecedented catastrophes are driven primarily by correlated losses. Our results show that the size and predictability of catastrophe losses pose less severe threats to insurers. Thus, we propose that first of all insurers and regulators should focus on measures that encourage diversification.

**Keywords:** Catastrophic Risks, Insurance Supply, Property/Casualty Insurance

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## 1 Introduction

Natural catastrophes pose a severe threat to insurance markets. We observe significant supply distortions in the aftermath of natural disasters when insurers tend to exit affected areas, which results in a lack of available coverage (Born & Viscusi, 2006; Born & Klimaszewski-Blettner, 2013; Grace & Klein, 2006, 2007). For instance, Allstate significantly reduced business in coastal states after Hurricane Katrina, while one of the largest personal insurers in Florida, Poe Financial, even became insolvent. Grace and Klein (2006, 2007) provide evidence that established insurers significantly reduced their supply of insurance coverage in high risk areas after the hurricane seasons 2004 and 2005. Apparently, despite of existing modelling techniques and a long history of disaster events, insurers can be surprised by new and devastating catastrophes. In this paper we infer how the availability of private market insurance can be ensured even in the aftermath of large scale and unprecedented catastrophes. For this, we first take a closer look at hazard specific insurance market reactions.

Although insurance market reactions after natural catastrophes have been analyzed extensively in recent years, to our knowledge there is no large-scale study which analyzes hazard-specific market reactions. Studies have either focused on one type of natural hazard (e.g. hurricanes; see e.g., Browne & Hoyt, 2000; Grace & Klein, 2009) or do not differentiate between different types of catastrophes at all (see e.g., Aseervatham, Born, & Richter, 2013; Born & Klimaszewski-Blettner, 2009; 2013; Thomann, 2013). The purpose of this research is to test whether there is one general type of insurance market reaction to natural catastrophes by comparing insurers' supply decisions after major tornado, hail storm and hurricane seasons. We argue that supply decisions might differ because the hazards vary in damage size, predictability and correlation[1] and analyze to what extent these characteristics drive the insurability problems in order to deduce recommendations to mitigate market distortions.

Past research stresses the importance of these characteristics: Born and Klimaszewski-Blettner (2013) find that the unexpected severity of a catastrophe is a main driver of exits in the homeowners insurance market. Klein and Kleindorfer (1999) also argue that the probable maximum loss of catastrophic events influences insurers supply decision heavily. Jaffee and Russell (1997) and Gollier (1997) argue that capital market imperfections are one of the main reasons that cause the related insurance supply problems. Hogarth and Kunreuther (1992) provide survey-based evidence that actuaries refuse to insure at all or insure correlated, and with regard to the probability ambiguous risks only at a very high price. In a related study, H. Kunreuther, Meszaros, Hogarth, and Spranca (1995) finds underwriters to be ambiguity

[1] Size, predictability, and correlation are often mentioned as important criteria of insurability (Berliner, 1982; Karten, 1997; H. C. Kunreuther & Michel-Kerjan, 2009; Klein & Kleindorfer, 1999).

averse with regard to probability and loss size. Grace and Klein (2006) argue that after Hurricane Andrew 1992, catastrophe modelling became more and more popular. This also can be seen as a measure to reduce the ambiguity with regard to loss size and probability of occurrence.

This research will achieve its purpose by examining how large-scale and unprecedented catastrophe losses in terms of property damages (adjusted for inflation) for each of the hazard types tornado, hurricane, and hail affect business volume, market exits, and underwriting performance of insurers in the United States over the period 1991-2012. By controlling for the size of the events and distinguishing between catastrophe types we will be able to identify to what extent the criteria predictability, correlation, and size influence insurers supply decisions. We gather insurer information from the NAIC database and catastrophe information from Sheldus™. To exploit the panel structure of our data we use a fixed-effects model, which is suggested by a Hausman Test. We also control for several insurer- and state-specific variables.

We find that even after controlling for the size of the natural hazards, hurricanes seem to cause the most severe problems for insurers. An insurer's probability to exit a state or reduce business by more than 60 % increases heavily after a severe hurricane season. In addition, an insurer's underwriting performance suffers three to four times stronger after hurricanes than after tornados or hails. The size of a natural catastrophe seems to matter, however correlated losses are the main driver for supply distortions. The evidence for market disruptions in the aftermath of extreme hail and tornado seasons is inconclusive. Thus, we suppose that insurers do not struggle with unclear predictions as much as with large and correlated losses.

The contribution of our paper is three folded: first, we provide a guideline for the evaluation of the results of prior catastrophe research. Since insurance supply reactions seem to differ between hazards, we conclude that generalizing results might be misleading. Further studies extending previous research seem to be worthwhile. Second, we infer which characteristics of catastrophes drive the availability constraints in the aftermath of natural disasters. In this paper, we find that correlation is a main factor to cause supply problems. Third, we are able to provide recommendations for where governmental intervention is needed or on what insurers should focus to ensure the availability of coverage. We argue that insurers and regulators should focus on diversification and the availability of risk capital in the first place. Apparently, the industry made progress with regard to catastrophe modelling, since the predictability of hazards seems to be less harmful for insurance companies.

The paper is structured as follows: Part two provides a brief overview of existing studies on the supply of insurance in the context of catastrophic risk. In part three, we develop our hypotheses. In part four and five we present our data and empirical method. In part six and seven we present our results and discuss those.

## 2 Supply-side Reactions in the Aftermath of Catastrophes

Prior literature on supply-side reactions after major natural disasters can be classified into two main categories. The first group of papers analyzes direct effects on prices and quantities in the market for natural catastrophe insurance. The second type of studies examines indirect effects on insurers' profitability and market valuation.

### 2.1 Price and Quantity

In general, insurers' risk-taking capacity is one crucial determinant for insurers' willingness to provide coverage. The "capacity constraint"-hypothesis assumes that insurers need to hold a sufficient amount of capital to meet regulatory requirements and/or avoid insolvency. Capital market imperfections can cause supply disruptions if the industry capacity is reduced by a negative external shock. Since natural catastrophe losses are equivalent to a negative shock to insurers' capital, the "capacity constraint"-hypothesis predicts a reduction of insurance supply immediately after major catastrophic losses (Gron, 1990; Winter, 1994; Gron, 1994; Cagle & Harrington, 1995). According to Cagle and Harrington (1995), the price effect of a negative shock to capital depends on the price elasticity of demand. The authors conclude that insurers' ability to recover from a catastrophic loss by increasing insurance prices is limited when policyholders respond to prices and insurers' default risk. Gron (1994) finds support for the "capacity-constraint"-hypothesis in the multi-peril insurance line and shows that catastrophic losses reduce insurers' underwriting margin.

In line with the "capacity-constraint"-hypothesis Born and Viscusi (2006) observe a negative supply effect of both large and unexpected catastrophes. Moreover, the authors find that insurers are able to improve their loss ratios in the medium term after "blockbuster catastrophes"[2] by raising insurance premiums. To some extent insurers seem to be able to shift the cost of a capital shock to the policyholders. The majority of their "blockbuster" events are hurricanes. It would be interesting to see whether we observe the same pattern for other disaster events. Since Klein and Kleindorfer (1999) and Grace and Klein (2009) who investigate the impact of hurricanes on the Florida insurance market receive similar results, the conjecture of a hurricane-specific effect might be supported. They find an increase in prices and a decrease in availability of insurance coverage because of the increased hurricane risk. Although larger insurers tend to reduce coverage after catastrophic losses, the authors still detect a remarkable risk of bankruptcies in this market since small regional, and consequently less-diversified insurers continue to underwrite huge amounts of hurricane

[2] The authors analyzed the 20 most costly natural disasters in the United States between 1984 and 2004.

risk. Grace, Klein, and Liu (2005) analyze insurance market reactions after the hurricane season of 2004 and 2005 and identify three major effects on insurance supply. Firstly, a reduction in insurers' and reinsurers' capital due to the loss shock, secondly an increase in the volatility of insurers' net income which aggravates the take up of new capital because of an increase in risk. Lastly, a disruption of insurers' confidence in their own risk assessment / risk models which might reduce their willingness to write new business. Moreover, the market concentration decreased in Florida, which is heavily exposed to hurricane risk. Thus, insurers try to mitigate hurricane risk through diversification.

In general, price increases after catastrophic events could be driven by both risk capital reduction and insurers' updating of the assumed risk exposure of the affected area, if they belief that a certain region will be affected more frequently or more severely in the future. Froot and O'Connell (1999) disentangle both effects by analyzing reinsurance prices in the aftermath of different types of natural catastrophes. Since they also observe price increases outside of the affected area independent of the actual exposure to a certain hazard, they conclude that capital market imperfections (a shortage of capital) are the main reason for the price increases.

Kleffner and Doherty (1996) examine the insurance market for earthquake risk in California and identify several determinants for insurers' capacity to write earthquake risk. Writing earthquake insurance increases the variance of insurer's cash-flows heavily since losses are highly correlated and impose large uncertainty on the insurer with respect to the parameters of the loss distribution. Consequently, Kleffner and Doherty find that high leverage and low diversification limit insurer's willingness to provide coverage. In addition, the organizational form and distribution system influence risk taking costs and as a result insurance supply decisions.

Thomann and von der Schulenburg (2006) show that the costs of risk bearing also determine the supply for terrorism reinsurance in Germany. In particular, the size of an insurance company matters. As larger insurers can easier diversify correlated risks, like a terrorist attack, they are more likely to provide coverage against this type of risk. In accordance with Kleffner and Doherty, the authors find also evidence for the importance of the ownership structure of an insurer.

Born and Klimaszewski-Blettner (2009) emphasize that there are different reactions in the commercial and the homeowners insurance markets in the aftermath of a catastrophe. The authors show that the homeowners business performs worse than the commercial business after a catastrophe. Born and Klimaszewski-Blettner (2013) analyze how the stricter regulatory environment in the homeowner's market influences insurers' response in the aftermath of natural disasters. Rate regulation and cancellation bans can cause severe supply disruption as insurers are exiting affected states or reduce business volume significantly after a catastrophic event. Importantly, the authors do not differentiate by type of disaster but pool over a variety of different hazards.

### 2.2 Profitability and Market Valuation

Besides direct effects on insurance prices and insurance supply, natural catastrophes affect insurers' market valuation, too. However, the impacts on insurers' stock prices seem to be ambiguous. Shelor, Anderson, and Cross (1992) find a positive effect of the 1989 California Earthquake on property-liability and multiple line insurers' market valuation. Despite of the indemnity payments, investors expect positive business prospects due to an increase in insurance demand. As a result, they observe an increase in insurers' stock prices independent of their actual written business in the affected area. Aiuppa, Carney, and Krueger (1993) confirm these findings in a related study. In contrast, Lamb (1995) shows that Hurricane Andrew had a negative impact on insurer stock values. However, only insurers who wrote business in Florida or Louisiana were affected. Unexposed insurers did not experience any stock price effect. Lamb argues that the stock market is able to interpret the new information of Hurricane Andrew efficiently. He explains the conflicting results in comparison to Shelor et al. (1992) and Aiuppa et al. (1993) with hazard-specific effects of hurricanes and earthquakes, respectively. Chen, Doerpinghaus, Lin, and Yu (2008) use the 9/11 terrorist attack to analyze the influence of catastrophic losses on insurers' profitability. By analyzing abnormal earnings forecast revisions the authors are able to detect two opposing effects of catastrophes on insurers' performance. In the short run insurers suffer from a claim effect since they did not expect a terrorist attack of this magnitude. However, insurers benefit in the long rung from a positive growth effect. Thomann (2013) examines insurers' stock price volatility and the correlation of insurers' stocks with the market in the aftermath of the 10 most expensive catastrophes in the U.S. In general, he detects an increase of insurance stocks' volatility which might bias the results of prior event studies after catastrophes. Interestingly, the correlation with the market decreases after natural catastrophes which have no influence on the general economy but increases after 9/11. This also supports the idea of disaster-specific consequences on the market valuation of insurance companies.

Table 1 provides an overview of catastrophe definitions used in prior studies. There is no general catastrophe definition but we observe two major approaches. Studies focus either on one single blockbuster event, like the 9/11 terrorist attacks, or use an arbitrary size criterion, e.g. 10 most costly events.

**Table 1**
Overview of Catastrophic Events Used in the Literature

| Author | Definition of Catastrophic Event | Hazard Differentiation |
|---|---|---|
| Shelor et al. (1992) | 1989 California Earthquake | Single Hazard |
| Aiuppa et al. (1993) | 1989 California Earthquake | Single Hazard |
| Lamb (1995) | Hurricane Andrew | Single Hazard |
| Froot and O'Connell (1999) | An event that gives rise to $15 million or more in insured losses. | Different hazards for each region |
| Born and Viscusi (2006) | 20 most costly natural catastrophes | Pooled Hazards |
| Chen et al. (2008) | WTC-attack | Single Hazard |
| Grace and Klein (2009)<br>Grace et al. (2005) | Hurricane season 2004 and 2005 | Single Hazard |
| Born and Klimaszewski-Blettner (2013) | Proxy for major disaster events: $\frac{\text{state wide damages from natural disasters}}{\text{all insurers' line specific premiums written in this state}} > 1$ | Pooled Hazards |
| Thomann (2013) | 10 most costly natural catastrophes | Differentiation between man-made and natural disaster damages |

In addition, the majority of papers do not examine differences between hazard-types. With few exceptions, they either focus on one disaster type or analyze the general impact of catastrophic losses. However, based on our cross-study comparisons both insurance and capital markets seem to respond differently depending on the disaster type. In the following, we show why supply reactions after hails, tornados, and hurricanes might differ.

## 3 Hazard-Specific Supply Reactions in the Aftermath of Natural Disasters

In the following we analyze hurricanes, hails, and tornados with respect to size, correlation, and predictability and derive predictions with regard to supply effects in the aftermath of catastrophes. In general, hail events and tornados have similarities in their characteristics, but show significant differences in comparison to hurricanes. In addition, hail and tornados often seem to occur at the same time (Agee et al., 1976, Davies-Jones, 1986, Paul &

McInnis, 2001). We assume that unprecedented disaster seasons[3] cause a reevaluation of an insurers risk exposure and might result in an adjustment in insurance supply.

**Size/Severity**

Hurricane, tornados, and hail events differ with regard to their severity. An analysis of the Sheldus™ data provides evidence that annual hurricane damages are on average about four to six times larger, in terms of annual property damage, than hail storms or tornados. Hail storms and tornados, on the other hand, are quite comparable with regard to severity. According to the capacity constraint hypothesis negative capital shocks could cause short term supply distortions with higher prices. Thus, one should expect *ceteris paribus* stronger supply reductions after hurricanes than after tornados and hails. In addition, we observe differences with respect to the standard deviation, maximum loss size and skewness. Table 2 presents the descriptive statistics of our hazard-specific natural catastrophe annual property damage data on state-level, which we discuss further below.

**Table 2**
Hazard-Specific Annual Property Damages per State for the years 1984 - 2012

| | Mean ($Mio.) | Std. ($Mio.) | Max. ($Mio.) | Skewness | Events | Events/ Observations |
|---|---|---|---|---|---|---|
| **Hail** | 13.6 | 76.5 | 1,360 | 11.20 | 1,034 | 0.71 |
| **Hurricane** | 80.3 | 1001 | 23,300 | 17.60 | 168 | 0.12 |
| **Tornado** | 21.7 | 147 | 4,220 | 21.47 | 1,068 | 0.73 |

**Correlation**

Even if we control for the size of the events, we still expect different reactions by insurers to different hazards. While tornados and hail storms appear all over the U.S. with a relatively high frequency (about 70 % of state-year observations in the period 1984-2012), hurricanes occur in about 12 % of the state-year observations and only in coastal states. Deryugina (2011) shows that hurricanes overwhelmingly affect nine states and barely occur outside this region. We suppose that diversification with regard to tornados is easier than diversification with regard to hurricanes, both in terms of temporal and regional diversification. Thus, again insurance supply should be reduced more heavily after hurricanes than after tornados and hails.

[3] In our empirical part, we analyze the impact of unprecedented hurricane, tornado, and hail seasons on insurers' supply. We define a state as hit by a major season if the annual property damages exceed the prior all-time maximum for any state.

**Ambiguity**

However, while the "hurricane season in the Atlantic begins June 1st and ends November 30th" (National Hurricane Center, 2014), "tornados have been known to occur in every state in the United States, on any day of the year, and at any hour" (National Severe Storms Laboratory, 2014). So there is much more ambiguity in assessing tornado risks than hurricane risks. This is also backed by the University Corporation for Atmospheric Research (UCAR), which "is a consortium of more than 100 member colleges and universities focused on research and training in the atmospheric and related Earth system sciences": Henson (2013) states that the NOAA's Storm Prediction Center publishes tornado forecasts 8 days in advance at maximum, whereas hurricane seasons can be already predicted up to one year. Henson also refers to a member of the NOAA who wants the Tornado outlooks "[…] to move toward something probabilistic, much like the hurricane outlooks". Several studies have shown that insurers are reluctant to sign ambiguous risks and thus, set a price markup (e.g., Kunreuther et al., 1995). If predictability is crucial for underwriting natural hazards, we should see strong insurance market reactions in the aftermath of heavy tornado seasons compared to hurricance seasons, of course after controlling for the size of the events. Additionally, if the skewness in annual property damages per state matters, we should see stronger reactions after extreme tornado years than hail years according to Table 2, since the informative value of the average damage for premium calculation is limited.

Our analysis can be summarized as in Table 3: while hurricanes cause more problems with regard to size and correlation, hail and tornados cause more predictability problems. Table 3 depicts the comparison of the insurability of these hazards. A positive sign in Table 3 represents a more demanding challenge for the insurer, while a negative sign represents a less important problem.

**Table 3**
Summary

| | Hurricane | Hail and Tornado |
|---|---|---|
| Size | + | - |
| Correlation | + | - |
| Predictability | - | + |

All these arguments support our hypothesis that different insurance market / supply reactions can be expected depending on the type of disaster.

Thus, our statistical hypothesis is:

*$H_0$: Supply reactions after catastrophes do not differ between hazard types even after controlling for the size of the event.*

By rejecting this hypothesis we are able to provide evidence for different supply reactions. The analysis of the characteristics will help us to derive implications for regulatory and insurer efforts and their ranking with regard to importance.

**4 Data**

The data set for our empirical analysis is a blend of two data sources. We received financial and underwriting information for all U.S. property insurers on state-level from the State Pages of insurers' annual filings with the National Association of Insurance Commissioners (NAIC). We obtained direct premiums earned and losses incurred for all homeowner and commercial (fire, allied and multiple peril lines) property insurers from 1991 to 2012. As we want to analyze the supply reaction of the entire insurance company within one state, we do not differentiate between lines and instead aggregate premiums earned and losses incurred on the firm-state level. General information about each insurance company in our data set, such as age, capacity (surplus), group affiliation, regional concentration and business mix[4], were also elicited from the same data source. In total, our data set consists of about 320,000 firm-state-year observations. Our sample consists of 2167 unique firms who were operating on average in about 12 different states and were on average active for 13 years.[5]

We supplement our data with information on the catastrophe experience of each state. Therefore, we compile natural disasters from Sheldus™, which provides hazard data for 18 different natural hazard event types at the county-level. To analyze the hazard-specific supply reactions of private insurance companies, we focus on three hazard types: hail storms, hurricanes and tornados. Although earthquakes and floods are also large-scale threats in the United States, we neglect them in our analysis, since they are covered, at least in some states, by government-sponsored insurance programs. These events should cause no or at least distorted private insurer supply reactions. Given that we are mainly interested in large catastrophe damages which threaten the financial viability of private insurers operating in an affected state, we compile the annual property damages[6] by hazard type and state. We classify a state as experiencing a catastrophic "hazard"-year if the annual property damages for a certain hazard exceeded the prior maximum for this hazard in any state. We introduce dummy variables for each hazard type ("*Major_Hurricane*", "*Major_Hail*", "*Major_Tornado*") which equal 1 if our event definition is met.[7] We use this event definition

[4] Number of lines in which the insurer operates within each state.
[5] To exclude inactive insurers we dropped firms with less than 1,000 $ premiums earned per year.
[6] All damages were expressed in 2012-dollars to account for inflated damages in more recent years.
[7] Consequently, the reference category is a combination of "minor hail, hurricane or tornado events", "floods", "earthquakes" , other hazards, and no events.

instead of a simple accounting for the occurrence of blockbuster events for several reasons. Firstly, we assume that policyholders pay less attention to the annual loss exposure of a state but are more focused on single devastating events. Therefore, we are able to reduce distorting effects caused by changes in insurance demand and as a result we are more likely to observe the unbiased supply reaction. Secondly, an event definition based on the size of single events would result in an overrepresentation of hurricanes which cause large-scale damages at one time. Thirdly, a lot of small or medium sized hazards in a year could also cause solvency problems for insurance companies – this would be ignored if only a single blockbuster event definition would be used. Insurers do not evaluate their underwriting performance based on a single event but compare the incurred losses in a year with their premium income in the respective year. Fourthly, insurers also have to rely on seasonal predictions rather than predictions on event basis, if at all. This also backs the aggregation of hazard damages on an annual basis (Henson, 2013).

To account for the fact that insurers elicit informational value from past events, we extend our natural catastrophe database to years before 1991. Therefore we apply our event definition already beginning in 1985 and classify a state as experiencing a major "hazard year" if the annual hazard specific property damages exceed the prior maximums beginning in 1985. According to Swiss Re (2014) damages caused by natural catastrophes increased dramatically since 1985. Table 4 provides a summary of events after applying our event definition for the entire time period. The dark grey-shaded year-state observations represent the event history, whereas the light grey-shaded observations are included in our analysis.[8]

Since we want to examine differences in insurers' reactions and performance in the aftermath of natural disasters depending on the hazard type, we focus our analysis on three criteria: business volume, the probability of exiting a state, and underwriting performance. We use two approaches to examine the impact of catastrophic events on the business volume of insurers operating in the affected state. Firstly, we analyze the direct impact on premiums earned. Secondly, we calculate the percentage change in premiums earned between the event year and the following year[9] and identify insurers who reduce their business by more than 60% and 80%. Business volume in a state is affected by both price and quantity effects. According to prior literature premiums tend to increase after a disaster event whereas the quantity of coverage decreases in disaster states. In contrast, if an insurer decides to leave an affected state, quantity will decrease by definition. For the sake of simplicity we classify in line with Born and Klimaszewski-Blettner (2013) an insurer as exiting a state if its premium earnings are zero in the following two years.

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[8] Without introducing an event history, the first year of our analysis (1991) would be an event year by definition.

[9] Specifically, $[PremiumsEarned(t+1) - PremiumsEarned(t)]/PremiumsEarned(t)$

**Table 4**

Summary of Catastrophic Events, 1985-2012

| Year | State | Annual property damages in Mio. $ | Hazard |
|---|---|---|---|
| 1985 | MS | 1030 | Hurricane |
| 1985 | OH | 127 | Tornado |
| 1986 | NE | 250 | Hail |
| 1989 | SC | 4940 | Hurricane |
| 1990 | CO | 834 | Hail |
| 1991 | KS | 185 | Tornado |
| 1996 | AR | 441 | Tornado |
| 1998 | FL | 510 | Tornado |
| 1999 | OK | 1460 | Tornado |
| 2001 | MO | 1300 | Hail |
| 2001 | TX | 6300 | Hurricane |
| 2004 | FL | 19500 | Hurricane |
| 2005 | LA | 23300 | Hurricane |
| 2011 | AL | 4220 | Tornado |
| 2012 | TX | 1360 | Hail |

This definition is fairly restrictive as only complete exits are captured. However, it does not differentiate between insolvencies, voluntary exits, M&A-transactions and other reasons which trigger an exit. Finally, we analyze insurers' ability to deal with different hazards by comparing the underwriting performance after different catastrophic events. We use $\frac{Premiums\ earned - Losses\ incurred}{Premiums\ earned}$ to measure the underwriting margin similar to Gron (1994) and Doherty/Garven (1995).

## 5 Empirical Model

The goal of our paper is to detect differences in insurers' supply reactions depending on the type of natural disaster. Therefore, we perform a series of panel-data regressions which analyze the effect of various variables on premiums earned, the probability of exiting a state, and underwriting performance. Our data are reported by firms on a state-level basis. Hence, each observation in our data set is a unique state-firm entity, and we control for time invariant unobserved heterogeneity by including firm-state fixed effects. Whether and how premiums are altered over time in response to changes in interest rates is heavily discussed in the literature (e.g.,Gron, 1994). We control for time-specific trends in our data set by including year dummies in our regression models. In addition, we add lagged variables (t-1; t-2) of our event dummies since insurers' supply reactions in the aftermath of a catastrophic event might emerge with some delay. For instance, cancelling policies or shutting down entire business operations within a state takes some time and is not possible immediately after a disaster occurred. Therefore, we think that analyzing the first and second year after a major catastrophic event is in particularly insightful. Additionally, we control for the size of the different hazards by including annual hazard-specific property damages within each state. We also use several corporate-specific variables $X_{it}$ as a control (reinsurance-ratio, surplus, company age, nation-wide premium income and number of lines).

Hence, we estimate our dependent variables (premiums earned, Pr(Exit), Pr(Business Reduction), Underwriting Performance) against our set of explanatory variables:

$$\begin{aligned}
\text{Dependent Variable}_{ist} & \\
= \beta_0 &+ \sum_{j=0}^{2} \beta_{j+1} * MajorHurricane_{s,t-j} + \sum_{j=0}^{2} \beta_{j+4} * MajorHail_{s,t-j} \\
&+ \sum_{j=0}^{2} \beta_{j+7} * MajorTornado_{s,t-j} \\
&+ \sum_{j=0}^{2} \beta_{j+10} * \ln(Prop.DmgHurricane)_{s,t-j} \\
&+ \sum_{j=0}^{2} \beta_{j+13} * \ln(Prop.DmgHail)_{s,t-j} \\
&+ \sum_{j=0}^{2} \beta_{j+16} * \ln(Prop.DmgTornado)_{s,t-j} + \gamma X_{it} + \sum_{j=1}^{22} \delta_j Y_j + \sum_{i=1}^{n} \mu_i F_i \\
&+ \varepsilon_{ist}
\end{aligned}$$

We use the same set of independent variables for all regression models. We run a linear fixed effects panel data regression for the premiums earned and underwriting equation with clustered standard errors. In contrast, we conduct a logistic panel data regression for the exit and business reduction probability[10].

[10] Due to our definition of an exit we lose another year of observations (2012). We estimate our model in Stata™ using the xtlogit command. Although the panel approach considers all insurers, insurers who never exit a state (i.d. dependent variable is always zero) are effectively dropped as they do not provide any information for the likelihood.

## 6 Results

The descriptive statistics of our data set are summarized in Table 5. We report our dependent variables and the number of lines within a state for each of our panel observations, the hazard data on state-year level, and all company specific control variables on firm-year level. Based on our data set and our definition of an exit we see insurers rarely leave states. The average insurer operates in multiple (about 17) lines within a state. The variable "Underwriting_Performance" exhibits strong variation. Some insurers perform very poorly in certain states and years, and face losses which exceed their premium income multiple times. In contrast to Table 2, we report only the hazard data which we used in our analysis. We capture all extreme years, which can be seen at the maximum values. In addition, the mean of the property damage variables is larger as compared to the full sample. Insurers seem to operate in about 12 states, nevertheless, we observe a strong variation between single state insurers and all state insurers. Interestingly, most insurers belong to a group.

The results of our first regression on the natural logarithm of premiums earned are summarized in Table 6. Since our main hypothesis assumes different supply reactions depending on the type of natural disasters, we focus our analysis on a comparison between the major hazard event-dummies. As we control for differences in the magnitude of the hazards by including the annual property damage exposure for each state and hazard, remaining differences have to be explained by other factors beyond damage size like the correlation of single damages or predictability problems. Interestingly, we observe an increase in business volumes in states affected by extreme hail-event years. In contrast, our results do not indicate any significant effects after tornado or hurricane years. The size of a catastrophe year seems to matter but the absolute size-effect on premiums earned is negligible. However, drawing conclusions based on premiums earned is always difficult since price and quantity effects might cause counteracting changes.

**Table 5**
Descriptive Statistics

| Variable | Obs | Mean | Std. | Min | Max |
|---|---|---|---|---|---|
| **Year-state-firm summary statistics:** | | | | | |
| Premiumsearned | 337,264 | 5,690,876 | 31,100,000 | 1,000.097 | 3,700,000,000 |
| EXITER | 318,207 | .0614757 | .2402012 | 0 | 1 |
| Business_Reduc_80 | 318,207 | .1327092 | .3392607 | 0 | 1 |
| Business_Reduc_60 | 318,207 | .1615992 | .3680833 | 0 | 1 |
| Underwriting performance | 337,264 | .355061 | 14.78901 | -3212.83 | 3094.978 |
| Number of lines within state | 337,232 | 16.95022 | 16.89059 | 0 | 55 |
| **State-Year summary statistics:** | | | | | |
| major hail | 1,100 | .0018182 | .0426207 | 0 | 1 |
| major hurricane | 1,100 | .0027273 | .0521758 | 0 | 1 |
| major tornado | 1,100 | .0045455 | .0672972 | 0 | 1 |
| hail_damages | 1,100 | 15,900,000 | 83,400,000 | 1 | 1,360,000,000 |
| hurricane_damages | 1,100 | 99,700,000 | 1,150,000,000 | 1 | 23,300,000,000 |
| tornado_damages | 1,100 | 26,400,000 | 168,000,000 | 1 | 4,220,000,000 |
| **Firm-Year summary statistics:** | | | | | |
| Number of states Insurer Operates | 29,151 | 11.56955 | 15.5077 | 1 | 50 |
| Group_Dummy | 29,151 | .7576756 | .4284969 | 0 | 1 |
| Nationwide Premiums Written | 29,151 | 242,000,000 | 768,000,000 | 1,068 | 18,400,000,000 |
| Age | 28,996 | 52.61757 | 44.35315 | 1 | 220 |
| Surplus | 29,008 | 216,000,000 | 1,060,000,000 | -3.39e+07 | 68,400,000,000 |

**Table 6**[11]

Fixed-effects Regression Results:
Dep. Variable = ln(Premiums Earned)

| | **ln(Premiums Earned)** |
|---|---|
| Explanatory Variables | Coefficient (Clustered Std. Error) |
| Major_Hail | 0.141*** |
| | [0.044] |
| Major_Hurricane | -0.059 |
| | [0.043] |
| Major_Tornado | 0.021 |
| | [0.029] |
| Major_Hail $_{(t-1)}$ | -0.019 |
| | [0.044] |
| Major_Hurricane $_{(t-1)}$ | -0.027 |
| | [0.044] |
| Major_Tornado $_{(t-1)}$ | 0.035 |
| | [0.030] |
| Major_Hail $_{(t-2)}$ | -0.002 |
| | [0.043] |
| Major_Hurricane $_{(t-2)}$ | -0.034 |
| | [0.039] |
| Major_Tornado $_{(t-2)}$ | -0.040 |
| | [0.034] |
| ln(Hail_Prop._Dmg) | -0.000 |
| | [0.001] |
| ln(Hurricane_Prop._Dmg) | 0.000 |
| | [0.001] |
| ln(Tornado_Prop._Dmg) | 0.000 |
| | [0.001] |
| ln(Hail_Prop._Dmg) $_{(t-1)}$ | -0.001** |
| | [0.001] |
| ln(Hurricane_Prop._Dmg) $_{(t-1)}$ | 0.001 |
| | [0.001] |
| ln(Tornado_Prop._Dmg) $_{(t-1)}$ | 0.001 |
| | [0.001] |
| ln(Hail_Prop._Dmg) $_{(t-2)}$ | -0.001 |
| | [0.001] |
| ln(Hurricane_Prop._Dmg) $_{(t-2)}$ | 0.002** |
| | [0.001] |
| ln(Tornado_Prop._Dmg) $_{(t-2)}$ | 0.002*** |
| | [0.001] |
| **Controls** | … |
| Observations | 315,182 |
| Number of panelvar | 41,678 |
| Adjusted R-squared | 0.191 |
| Insurer FE | YES |
| Year FE | YES |

**Note:** Regression results include firm-state fixed effects, year dummies, and further controls, not shown *, **, and *** denote significance at the 90%, 95%, and 99% level, two-tailed test.

[11] Please refer to the appendix for complete version of our regression table.

In order to analyze changes in insurers' willingness to provide coverage in the aftermath of catastrophic events more thoroughly, we focus in our second set of regressions on the probability of exiting a state and the probability of reducing business operations dramatically. Our results are summarized in Table 7.

**Table 7**
Logit Results: Dependent Variable= Insurer Exit / Business Reduction of more than 60% or 80%

| Explanatory Variables | **Pr(Exit)** Coefficient (Std. Error) | **Pr(Bus._Reduc80)** Coefficient (Std. Error) | **Pr(Bus._Reduc60)** Coefficient (Std. Error) |
|---|---|---|---|
| Major_Hail | -0.095 | 0.172 | 0.175 |
| | [0.266] | [0.186] | [0.175] |
| Major_Hurricane | 0.325* | 0.098 | 0.055 |
| | [0.167] | [0.115] | [0.108] |
| Major_Tornado | -0.131 | 0.005 | -0.010 |
| | [0.146] | [0.097] | [0.090] |
| Major_Hail $_{(t-1)}$ | 0.171 | 0.267* | 0.232* |
| | [0.212] | [0.137] | [0.131] |
| Major_Hurricane $_{(t-1)}$ | 0.341 | 0.225* | 0.342*** |
| | [0.211] | [0.127] | [0.112] |
| Major_Tornado $_{(t-1)}$ | -0.071 | -0.035 | -0.056 |
| | [0.160] | [0.108] | [0.102] |
| Major_Hail $_{(t-2)}$ | -0.589** | -0.294* | -0.193 |
| | [0.261] | [0.156] | [0.146] |
| Major_Hurricane $_{(t-2)}$ | 0.230 | 0.361*** | 0.132 |
| | [0.178] | [0.114] | [0.104] |
| Major_Tornado $_{(t-2)}$ | 0.174 | 0.118 | 0.111 |
| | [0.147] | [0.102] | [0.095] |
| ln(Hail_Prop._Dmg) | 0.000 | 0.004*** | 0.003* |
| | [0.003] | [0.002] | [0.002] |
| ln(Hurricane_Prop._Dmg) | 0.005** | 0.008*** | 0.006*** |
| | [0.003] | [0.002] | [0.002] |
| ln(Tornado_Prop._Dmg) | -0.003 | 0.001 | -0.000 |
| | [0.003] | [0.002] | [0.002] |
| ln(Hail_Prop._Dmg) $_{(t-1)}$ | 0.005** | 0.002 | 0.002 |
| | [0.003] | [0.002] | [0.002] |
| ln(Hurricane_Prop._Dmg) $_{(t-1)}$ | -0.001 | 0.004** | 0.002 |
| | [0.003] | [0.002] | [0.002] |
| ln(Tornado_Prop._Dmg) $_{(t-1)}$ | -0.004 | -0.003* | -0.002 |
| | [0.003] | [0.002] | [0.002] |
| ln(Hail_Prop._Dmg) $_{(t-2)}$ | -0.000 | -0.000 | 0.000 |
| | [0.003] | [0.002] | [0.002] |
| ln(Hurricane_Prop._Dmg) $_{(t-2)}$ | 0.004 | 0.002 | 0.002 |
| | [0.003] | [0.002] | [0.002] |
| ln(Tornado_Prop._Dmg) $_{(t-2)}$ | -0.004 | 0.001 | 0.001 |
| | [0.003] | [0.002] | [0.002] |
| **Controls** | … | … | … |
| Observations | 90,579 | 163,808 | 182,832 |
| Number of panelvar | 12,088 | 18,877 | 20,800 |
| Pseudo-R2 | 0.118 | 0.0737 | 0.0667 |
| Insurer FE | YES | YES | YES |
| Year FE | YES | YES | YES |

**Note:** Regression results include firm-state fixed effects, year dummies and further controls, not shown. *, **, and *** denote significance at the 90%, 95%, and 99% level, two-tailed test.

First of all, extreme hurricane years increase the probability to exit an affected state significantly. Tornado and hail years seem to lower the probability to exit. In particular, two years after a major hail year there is a significant negative effect on the exit probability. While the size of hurricanes and hail storms increase the probability to exit a state, size of a tornado does not affect the decision to leave the market.

However, an insurance company usually cannot change its strategy immediately in the aftermath of a catastrophic event. An insurer can stop writing new policies and refrain from renewing expired policies but an immediate cancellation of in-force business is not possible. In addition, shutting down entire business operations in a state is even more time-consuming. Therefore, we examine large-scale reductions of business volume besides the analysis of complete exits. Again we do not see any significant influence of tornado years but hurricanes have a strong negative and persistent effect on insurers' supply decision in disaster regions. Interestingly, the impact of extreme hail years is less clear. In the short run, one year after an event, insurers are more likely to downsize their business operations in affected states. However, this effect disappears or even lowers the business reduction probability two years after the loss event. Not surprisingly, the size of hurricane and hail events affects the probability to downsize the risk exposure significantly.

Our results suggest that extreme hurricane years cause insurers' exits and result in significant downsizing of available coverage. In line with our prior findings extreme tornado years seem to have no direct effects on insurers' supply. The results for extreme hail storm years are less conclusive. Insurers seem to reduce their business volume but in the medium term insurers are less likely to exit an affected state.

We estimate our set of independent variables on "Underwriting_Performance" to show differences in insurers' ability to deal with different hazards. Our results are summarized in Table 8.

All major event years reduce insurers' underwriting performance immediately and significantly. Therefore, our event definition seems to capture extreme loss events from the insurers' perspective. However, the impact of extreme hurricane years is about three to four times as strong as the effect of other hazards. In addition, insurers operating in a state hit by a major hurricane experience a more persistent decrease in their underwriting performance. The hazard-specific damage-size influences the underwriting performance of individual insurers only weakly and in no consistent pattern.

**Table 8**
Fixed-effects Regression Results: Dep. Variable = Underwriting Performance

| Explanatory Variables | Underwriting_Perf Coefficient (Clustered Std. Error) |
|---|---|
| Major_Hail | -0.416** |
| | [0.209] |
| Major_Hurricane | -1.306*** |
| | [0.261] |
| Major_Tornado | -0.320 |
| | [0.195] |
| Major_Hail $_{(t-1)}$ | -0.095 |
| | [0.193] |
| Major_Hurricane $_{(t-1)}$ | -0.635** |
| | [0.283] |
| Major_Tornado $_{(t-1)}$ | -0.318** |
| | [0.159] |
| Major_Hail $_{(t-2)}$ | -0.164 |
| | [0.127] |
| Major_Hurricane $_{(t-2)}$ | -2.249 |
| | [1.774] |
| Major_Tornado $_{(t-2)}$ | 0.010 |
| | [0.061] |
| ln(Hail_Prop._Dmg) | -0.006 |
| | [0.005] |
| ln(Hurricane_Prop._Dmg) | -0.010 |
| | [0.008] |
| ln(Tornado_Prop._Dmg) | -0.012** |
| | [0.006] |
| ln(Hail_Prop._Dmg) $_{(t-1)}$ | 0.012** |
| | [0.006] |
| ln(Hurricane_Prop._Dmg) $_{(t-1)}$ | 0.003 |
| | [0.009] |
| ln(Tornado_Prop._Dmg) $_{(t-1)}$ | -0.000 |
| | [0.007] |
| ln(Hail_Prop._Dmg) $_{(t-2)}$ | -0.007 |
| | [0.010] |
| ln(Hurricane_Prop._Dmg) $_{(t-2)}$ | 0.003 |
| | [0.006] |
| ln(Tornado_Prop._Dmg) $_{(t-2)}$ | -0.012 |
| | [0.008] |
| **Controls** | … |
| Observations | 315,182 |
| Number of panelvar | 41,678 |
| Adjusted R-squared | 0.000159 |
| Insurer FE | YES |
| Year FE | YES |

**Note:** Regression results include firm-state fixed effects, year dummies, and further controls, not shown *, **, and *** denote significance at the 90%, 95%, and 99% level, two-tailed test.

### Robustness Checks

As wealthier states might face larger property damages but also have larger capacities to deal with them, we normalize the annual property damages by the per-capita-income of each state in our major hazard year identification process. The results are presented in the Appendix (Tables A.4, A.5, and A.6). In the premiums regression, the hail event year loses its significance. The impact of hurricanes on exits and business reduction in general is supported and strengthened by our robustness check. The inconclusive effect of hail events can also be found when the event identification is modified. The per capita adjusted model also backs the strong negative and persistent influence of hurricanes on the underwriting performance.

More populated states tend to have higher property damages. That's why we conducted an additional robustness check using the state wide population to normalize property damages in our major hazard year identification process. The results are also presented in the Appendix (Tables A.4, A.5, and A.6). Hails and hurricanes seem to impact premiums negatively two years after the devastating season. Interestingly, hurricanes now seem to reduce exits, but increase downsizing of business. Hails lose their inconclusiveness – they only seem to increase business reduction in the short term. Interestingly, hurricanes do not seem to influence the underwriting performance of insurers, whereas hails and tornadoes do. These events seem to have severe negative impact on the loss ratios. In general, we find that the population adjusted model is only partially supportive for our evidence. However, these results have to be treated with caution, because this approach would overweight smaller states whose damages would not threaten the financial viability of an insurer.

### Limitations

As all other catastrophe definitions our approach is to some extent arbitrary – however, our results are overwhelmingly stable to changes in this definition. We conducted robustness checks using an income and population adjusted catastrophe definition and received quite similar results. Demand effects might disturb our analysis although we try to minimize this problem by our catastrophe definition. As we only identify directly affected states we neglect potential spill-over effects. However, this should rather lead to an underestimation of the effects in our analysis and thus, support our results.

## 7 Discussion and Policy Implications

In this paper we were able to show that the type of a natural disaster matters for insurers' supply reactions with regard to business volume, exits and underwriting performance. We investigated how insurers are affected after large and unprecedented hazard seasons. In general, major hurricane seasons have stronger and longer lasting effects on insurers' supply decisions compared with the other hazards in our analysis. Even after controlling for the size of the annual property damages we observe significant differences in the probability to exit a state or probability to reduce business. Furthermore, insurers' underwriting performance seems to suffer more after hurricane events. Based on these findings we conclude that it is easier for insurers to deal with extreme hail or tornado years. As mentioned before, hurricanes occur in a fairly restricted area, and therefore insurers' benefits from regional diversification are very limited. Since we account for the size of the hazard damages, the remaining difference between hurricanes, tornados, and hails can be traced back to the degree of correlation between single loss events. Thus, we recommend insurers and regulators to focus on encouraging diversification. Currently writing business in different states is hindered due to state specific regulation. Insurers might refrain from achieving diversification by operating in multiple states, since adapting products and processes to the local regulatory framework might be too costly. According to Ibragimov et al. (2008) diversification benefits for heavy-tailed risks might exhibit a u-shaped relationship. Thus, an increase in the number of risks might even have a negative impact on the individual insurer's performance. On the industry level, diversification benefits remain positive. The authors recommend a central agency to achieve coordinated diversification equilibria and unleash diversification benefits. An obvious way to increase diversification is through incentivizing the purchase of reinsurance coverage, lowering reinsurance requirements, or implementing tax benefits for reinsurance. In particular, international reinsurers could enhance the worldwide diversification of catastrophic risks. Another way to reduce supply problems due to poor diversification is by implementing all hazard insurance policies (Kunreuther and Michel-Kerjan, 2009). Insurers could benefit from bundling more and less frequent risks all over the U.S.

We also identified size to be a criterion of insurability. Not surprisingly, we find that the larger the hazard the more supply distortions are caused. However, this effect seems to be fairly small relative to the correlation impact. Of course, measures enhancing the risk taking capacity of insurers could be beneficial. But according to our analysis this measures should not be addressed with the highest priority. One way to enhance insurer's ability to deal with large scale risks is to reduce the cost of holding risk capital. Jaffee and Russell (1997) and Gollier (1997) argue that capital market imperfections are one of the main reasons that cause the related insurance supply problems.

The predictability of natural catastrophes is also mentioned as a challenge when insuring catastrophic risks. We do not find clear evidence for this. We suppose that the huge efforts of the insurance industry with regard to catastrophe modelling and prediction might explain our results. So, investing in event and seasonal prediction as well as catastrophe modelling currently should not have the highest priority, although improving the existing measures remains an ongoing task.

Taking into account the results of our empirical analysis, we are able to reject our null hypothesis since insurers' supply reactions differ significantly with respect to the type of hazard. We conclude that results based on one-hazard studies should not be generalized to other hazards since insurers are very likely to react differently after catastrophic events with the same size in terms of damages but with a different trigger. In addition, prior studies which examined the influence of different natural hazards on insurance markets within one analysis without differentiating between the types of hazards could be extended. Differentiating between hazards might provide additional insights.

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## Appendix

**Table A.1**
Fixed-effects Regression Results: Dep. Variable = ln(Premiums Earned)

| VARIABLES | (1)<br>log_Premiumsearned |
|---|---|
| Major_Hail | 0.141*** |
| | [0.044] |
| Major_Hurricane | -0.059 |
| | [0.043] |
| Major_Tornado | 0.021 |
| | [0.029] |
| Major_Hail $_{(t-1)}$ | -0.019 |
| | [0.044] |
| Major_Hurricane $_{(t-1)}$ | -0.027 |
| | [0.044] |
| Major_Tornado $_{(t-1)}$ | 0.035 |
| | [0.030] |
| Major_Hail $_{(t-2)}$ | -0.002 |
| | [0.043] |
| Major_Hurricane $_{(t-2)}$ | -0.034 |
| | [0.039] |
| Major_Tornado $_{(t-2)}$ | -0.040 |
| | [0.034] |
| log_hail_propdmg | -0.000 |
| | [0.001] |
| log_hurricane_propdmg | 0.000 |
| | [0.001] |
| log_tornado_propdmg | 0.000 |
| | [0.001] |
| llog_hail_propdmg | -0.001** |
| | [0.001] |
| llog_hurricane_propdmg | 0.001 |
| | [0.001] |
| llog_tornado_propdmg | 0.001 |
| | [0.001] |
| lllog_hail_propdmg | -0.001 |
| | [0.001] |
| lllog_hurricane_propdmg | 0.002** |
| | [0.001] |
| lllog_tornado_propdmg | 0.002*** |
| | [0.001] |
| nlines | 0.001 |
| | [0.002] |
| group | 0.164** |
| | [0.073] |
| log_NatPremsitadj | 0.784*** |
| | [0.029] |
| age | 0.004** |

| | |
|---|---|
| | [0.002] |
| surplus | 0.000 |
| | [0.000] |
| reinsurance | -0.033 |
| | [0.076] |
| Constant | -2.380*** |
| | [0.556] |
| | |
| Observations | 315,182 |
| Number of panelvar | 41,678 |
| Adjusted R-squared | 0.191 |
| Insurer FE | YES |
| Year FE | YES |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A.2**

Logit Results: Dependent Variable= Insurer Exit / Business Reduction of more than 60% or 80%

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | EXITER | BUSINESSREDUCTION80 | BUSINESSREDUCTION60 |
| Major_Hail | -0.095 | 0.172 | 0.175 |
| | [0.266] | [0.186] | [0.175] |
| Major_Hurricane | 0.325* | 0.098 | 0.055 |
| | [0.167] | [0.115] | [0.108] |
| Major_Tornado | -0.131 | 0.005 | -0.010 |
| | [0.146] | [0.097] | [0.090] |
| Major_Hail $_{(t-1)}$ | 0.171 | 0.267* | 0.232* |
| | [0.212] | [0.137] | [0.131] |
| Major_Hurricane $_{(t-1)}$ | 0.341 | 0.225* | 0.342*** |
| | [0.211] | [0.127] | [0.112] |
| Major_Tornado $_{(t-1)}$ | -0.071 | -0.035 | -0.056 |
| | [0.160] | [0.108] | [0.102] |
| Major_Hail $_{(t-2)}$ | -0.589** | -0.294* | -0.193 |
| | [0.261] | [0.156] | [0.146] |
| Major_Hurricane $_{(t-2)}$ | 0.230 | 0.361*** | 0.132 |
| | [0.178] | [0.114] | [0.104] |
| Major_Tornado $_{(t-2)}$ | 0.174 | 0.118 | 0.111 |
| | [0.147] | [0.102] | [0.095] |
| log_hail_propdmg | 0.000 | 0.004*** | 0.003* |
| | [0.003] | [0.002] | [0.002] |
| log_hurricane_propdmg | 0.005** | 0.008*** | 0.006*** |
| | [0.003] | [0.002] | [0.002] |
| log_tornado_propdmg | -0.003 | 0.001 | -0.000 |
| | [0.003] | [0.002] | [0.002] |
| llog_hail_propdmg | 0.005** | 0.002 | 0.002 |
| | [0.003] | [0.002] | [0.002] |
| llog_hurricane_propdmg | -0.001 | 0.004** | 0.002 |
| | [0.003] | [0.002] | [0.002] |
| llog_tornado_propdmg | -0.004 | -0.003* | -0.002 |
| | [0.003] | [0.002] | [0.002] |
| lllog_hail_propdmg | -0.000 | -0.000 | 0.000 |
| | [0.003] | [0.002] | [0.002] |
| lllog_hurricane_propdmg | 0.004 | 0.002 | 0.002 |
| | [0.003] | [0.002] | [0.002] |
| lllog_tornado_propdmg | -0.004 | 0.001 | 0.001 |
| | [0.003] | [0.002] | [0.002] |
| nlines | -0.006*** | -0.007*** | -0.007*** |
| | [0.001] | [0.001] | [0.001] |
| group | -0.038 | 0.193*** | 0.261*** |
| | [0.085] | [0.055] | [0.051] |
| log_NatPremsitadj | -0.835*** | -0.541*** | -0.488*** |
| | [0.017] | [0.012] | [0.011] |
| age | -0.015*** | -0.010*** | -0.009*** |
| | [0.001] | [0.001] | [0.001] |
| surplus | -0.000*** | -0.000*** | -0.000*** |
| | [0.000] | [0.000] | [0.000] |
| reinsurance | 0.760*** | 0.520*** | 0.449*** |

| | | | |
|---|---|---|---|
| | [0.064] | [0.044] | [0.041] |
| | | | |
| Observations | 90,579 | 163,808 | 182,832 |
| Number of panelvar | 12,088 | 18,877 | 20,800 |
| Insurer FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| d. f. | 43 | 43 | 43 |
| Log-Likelihood | -21977 | -50217 | -59069 |
| Chi2 | 5863 | 7995 | 8437 |
| p-Value | 0 | 0 | 0 |
| Pseudo-R2 | 0.118 | 0.0737 | 0.0667 |

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A.3**
Fixed-effects Regression Results: Dep. Variable = Underwriting Performance

| VARIABLES | (1) Underwritingperf |
|---|---|
| majoreventstatehail | -0.416** |
| | [0.209] |
| majoreventstatehurricane | -1.306*** |
| | [0.261] |
| majoreventstatetornado | -0.320 |
| | [0.195] |
| lmajoreventstatehail | -0.095 |
| | [0.193] |
| lmajoreventstatehurricane | -0.635** |
| | [0.283] |
| lmajoreventstatetornado | -0.318** |
| | [0.159] |
| llmajoreventstatehail | -0.164 |
| | [0.127] |
| llmajoreventstatehurricane | -2.249 |
| | [1.774] |
| llmajoreventstatetornado | 0.010 |
| | [0.061] |
| log_hail_propdmg | -0.006 |
| | [0.005] |
| log_hurricane_propdmg | -0.010 |
| | [0.008] |
| log_tornado_propdmg | -0.012** |
| | [0.006] |
| llog_hail_propdmg | 0.012** |
| | [0.006] |
| llog_hurricane_propdmg | 0.003 |
| | [0.009] |
| llog_tornado_propdmg | -0.000 |
| | [0.007] |
| lllog_hail_propdmg | -0.007 |
| | [0.010] |
| lllog_hurricane_propdmg | 0.003 |
| | [0.006] |
| lllog_tornado_propdmg | -0.012 |
| | [0.008] |
| nlines | 0.001 |
| | [0.008] |
| group | -0.169** |
| | [0.080] |
| log_NatPremsitadj | -0.126 |
| | [0.138] |
| age | -0.017 |
| | [0.013] |
| surplus | 0.000 |
| | [0.000] |
| reinsurance | 0.005 |
| | [0.119] |
| Constant | 4.046 |

| | |
|---|---|
| | [2.645] |
| | |
| Observations | 315,182 |
| Number of panelvar | 41,678 |
| R-squared | 0.000 |
| Insurer FE | YES |
| Year FE | YES |
| Adj. R-squared | 0.000159 |
| F value | . |
| d.f. | 44 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A.4**
Fixed-effects Regression Results: Dep. Variable = ln(Premiums Earned)

| | Population_adj damages | Per capita income_adj damages |
|---|---|---|
| VARIABLES | log_Premiumsearned | log_Premiumsearned |
| Major_Hail | 0.061 | 0.040 |
| | [0.066] | [0.047] |
| Major_Hurricane | 0.030 | -0.063 |
| | [0.068] | [0.058] |
| Major_Tornado | -0.015 | -0.015 |
| | [0.031] | [0.031] |
| Major_Hail $_{(t-1)}$ | 0.019 | -0.023 |
| | [0.052] | [0.044] |
| Major_Hurricane $_{(t-1)}$ | -0.006 | 0.052 |
| | [0.072] | [0.056] |
| Major_Tornado $_{(t-1)}$ | 0.006 | 0.006 |
| | [0.032] | [0.032] |
| Major_Hail $_{(t-2)}$ | -0.095* | -0.005 |
| | [0.055] | [0.043] |
| Major_Hurricane $_{(t-2)}$ | -0.115** | 0.001 |
| | [0.057] | [0.047] |
| Major_Tornado $_{(t-2)}$ | -0.049 | -0.049 |
| | [0.037] | [0.037] |
| ln(Hail_Prop._Dmg) | -0.000 | -0.000 |
| | [0.001] | [0.001] |
| ln(Hurricane_Prop._Dmg) | -0.000 | -0.000 |
| | [0.001] | [0.001] |
| ln(Tornado_Prop._Dmg) | 0.000 | 0.000 |
| | [0.001] | [0.001] |
| ln(Hail_Prop._Dmg) $_{(t-1)}$ | -0.001** | -0.001** |
| | [0.001] | [0.001] |
| ln(Hurricane_Prop._Dmg) $_{(t-1)}$ | 0.000 | 0.000 |
| | [0.001] | [0.001] |
| ln(Tornado_Prop._Dmg) $_{(t-1)}$ | 0.001 | 0.001 |
| | [0.001] | [0.001] |
| ln(Hail_Prop._Dmg) $_{(t-2)}$ | -0.001 | -0.001 |
| | [0.001] | [0.001] |
| ln(Hurricane_Prop._Dmg) $_{(t-2)}$ | 0.002*** | 0.002*** |
| | [0.001] | [0.001] |
| ln(Tornado_Prop._Dmg) $_{(t-2)}$ | 0.001*** | 0.001** |
| | [0.001] | [0.001] |
| nlines | 0.001 | 0.001 |
| | [0.002] | [0.002] |
| group | 0.164** | 0.164** |
| | [0.073] | [0.073] |
| log_NatPremsitadj | 0.784*** | 0.784*** |
| | [0.029] | [0.029] |
| age | 0.004** | 0.004** |
| | [0.002] | [0.002] |
| surplus | 0.000 | 0.000 |

| | | |
|---|---|---|
| | [0.000] | [0.000] |
| reinsurance | -0.033 | -0.033 |
| | [0.076] | [0.076] |
| Observations | 315,182 | 315,182 |
| R-squared | 0.191 | 0.191 |
| Number of panelvar | 41,678 | 41,678 |
| Insurer FE | YES | YES |
| Year FE | YES | YES |
| Adj. R-squared | 0.191 | 0.191 |
| F value | . | . |
| d.f. | 44 | 44 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A.5**
Logit Results: Dependent Variable= Insurer Exit / Business Reduction of more than 60% or 80%

| VARIABLES | Population_adj damages EXITER | Per capita income_adj damages EXITER | Population_adj damages BUSINESS REDUCTION80 | Per capita income_adj damages BUSINESS REDUCTION80 | Population_adj damages BUSINESS REDUCTION60 | Per capita income_adj damages BUSINESS REDUCTION60 |
|---|---|---|---|---|---|---|
| Major_Hail | -0.222 | -0.105 | -0.069 | 0.172 | 0.045 | 0.003* |
| | [0.320] | [0.265] | [0.217] | [0.186] | [0.202] | [0.002] |
| Major_Hurricane | -0.898* | 0.186 | 0.555*** | -0.070 | 0.681*** | 0.006*** |
| | [0.543] | [0.247] | [0.195] | [0.152] | [0.184] | [0.002] |
| Major_Tornado | -0.181 | -0.185 | 0.032 | 0.037 | 0.039 | -0.000 |
| | [0.173] | [0.173] | [0.114] | [0.114] | [0.105] | [0.002] |
| Major_Hail (t-1) | -0.140 | 0.168 | 0.229 | 0.266* | 0.306** | 0.002 |
| | [0.248] | [0.212] | [0.147] | [0.137] | [0.139] | [0.002] |
| Major_Hurricane (t-1) | -0.358 | 0.608** | 0.323 | 0.438*** | 0.288 | 0.003* |
| | [0.562] | [0.308] | [0.330] | [0.160] | [0.279] | [0.002] |
| Major_Tornado (t-1) | -0.178 | -0.184 | -0.005 | -0.007 | -0.040 | -0.002 |
| | [0.194] | [0.194] | [0.129] | [0.129] | [0.123] | [0.002] |
| Major_Hail (t-2) | -0.262 | -0.591** | 0.081 | -0.299* | 0.076 | 0.000 |
| | [0.238] | [0.261] | [0.150] | [0.156] | [0.144] | [0.002] |
| Major_Hurricane (t-2) | 0.194 | 0.347 | 0.061 | 0.413*** | -0.026 | 0.003 |
| | [0.267] | [0.224] | [0.173] | [0.142] | [0.147] | [0.002] |
| Major_Tornado (t-2) | 0.077 | 0.074 | 0.128 | 0.131 | 0.140 | 0.001 |
| | [0.175] | [0.175] | [0.121] | [0.121] | [0.113] | [0.002] |
| ln(Hail_Prop._Dmg) | 0.000 | 0.000 | 0.005*** | 0.004** | 0.003* | -0.007*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.001] |
| ln(Hurricane_Prop._Dmg) | 0.007*** | 0.006** | 0.008*** | 0.008*** | 0.006*** | 0.262*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.051] |
| ln(Tornado_Prop._Dmg) | -0.002 | -0.002 | 0.001 | 0.001 | -0.000 | -0.489*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.011] |
| ln(Hail_Prop._Dmg) (t-1) | 0.005** | 0.005** | 0.003 | 0.002 | 0.002 | -0.009*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.001] |
| ln(Hurricane_Prop._Dmg) (t-1) | 0.000 | -0.001 | 0.004** | 0.004** | 0.003* | -0.000*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.000] |
| ln(Tornado_Prop._Dmg) (t-1) | -0.004 | -0.004 | -0.003* | -0.003 | -0.002 | 0.449*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.041] |
| ln(Hail_Prop._Dmg) (t-2) | -0.001 | -0.000 | -0.000 | -0.000 | 0.000 | 0.000 |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.000] |
| ln(Hurricane_Prop._Dmg) (t-2) | 0.004 | 0.003 | 0.002 | 0.002 | 0.002 | 0.091** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.041] |
| ln(Tornado_Prop._Dmg) (t-2) | -0.003 | -0.004 | 0.001 | 0.001 | 0.001 | 0.270*** |
| | [0.003] | [0.003] | [0.002] | [0.002] | [0.002] | [0.041] |
| nlines | -0.006*** | -0.006*** | -0.007*** | -0.007*** | -0.007*** | 0.280*** |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.042] |
| group | -0.039 | -0.037 | 0.195*** | 0.193*** | 0.262*** | 0.414*** |
| | [0.085] | [0.085] | [0.055] | [0.055] | [0.051] | [0.042] |
| log_NatPremsitadj | -0.835*** | -0.835*** | -0.541*** | -0.541*** | -0.488*** | 0.571*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | [0.017] | [0.017] | [0.012] | [0.012] | [0.011] | [0.043] |
| age | -0.014*** | -0.014*** | -0.010*** | -0.010*** | -0.009*** | 0.585*** |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.043] |
| surplus | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** | 0.673*** |
| | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.043] |
| reinsurance | 0.762*** | 0.760*** | 0.520*** | 0.519*** | 0.449*** | 0.791*** |
| | [0.064] | [0.064] | [0.044] | [0.044] | [0.041] | [0.044] |
| Observations | 90,579 | 90,579 | 163,808 | 163,808 | 182,832 | 182,832 |
| Number of panelvar | 12,088 | 12,088 | 18,877 | 18,877 | 20,800 | 20,800 |
| Insurer FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| d. f. | 43 | 43 | 43 | 43 | 43 | 43 |
| Log-Likelihood | -21981 | -21977 | -50222 | -50215 | -59067 | -59070 |
| Chi2 | 5855 | 5862 | 7985 | 7998 | 8440 | 8436 |
| p-Value | 0 | 0 | 0 | 0 | 0 | 0 |
| Pseudo-R2 | 0.118 | 0.118 | 0.0736 | 0.0738 | 0.0667 | 0.0666 |

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

**Table A.5**
Fixed-effects Regression Results: Dep. Variable = Underwriting Performance

| VARIABLES | Population_adj damages<br>Underwritingperf | Per capita income_adj damages<br>Underwritingperf |
|---|---|---|
| Major_Hail | -0.471*** | -0.417** |
| | [0.145] | [0.183] |
| Major_Hurricane | -0.642 | -2.057*** |
| | [0.813] | [0.368] |
| Major_Tornado | -0.426 | -0.417 |
| | [0.352] | [0.353] |
| Major_Hail (t-1) | -0.196** | -0.102 |
| | [0.092] | [0.197] |
| Major_Hurricane (t-1) | 0.631 | -0.955*** |
| | [0.818] | [0.368] |
| Major_Tornado (t-1) | -0.422*** | -0.389*** |
| | [0.150] | [0.148] |
| Major_Hail (t-2) | 0.147 | -0.138 |
| | [0.130] | [0.129] |
| Major_Hurricane (t-2) | -1.746 | -3.171 |
| | [1.339] | [2.605] |
| Major_Tornado (t-2) | -0.027 | -0.011 |
| | [0.069] | [0.070] |
| log_hail_propdmg | -0.007 | -0.006 |
| | [0.005] | [0.005] |
| log_hurricane_propdmg | -0.016** | -0.013* |
| | [0.008] | [0.008] |
| log_tornado_propdmg | -0.012* | -0.012** |
| | [0.006] | [0.006] |
| llog_hail_propdmg | 0.012* | 0.013** |
| | [0.006] | [0.006] |
| llog_hurricane_propdmg | 0.001 | 0.003 |
| | [0.007] | [0.008] |
| llog_tornado_propdmg | -0.000 | -0.000 |
| | [0.008] | [0.008] |
| lllog_hail_propdmg | -0.007 | -0.007 |
| | [0.010] | [0.010] |
| lllog_hurricane_propdmg | -0.001 | 0.003 |
| | [0.008] | [0.005] |
| lllog_tornado_propdmg | -0.012 | -0.013 |
| | [0.008] | [0.008] |
| nlines | 0.001 | 0.001 |
| | [0.008] | [0.008] |
| group | -0.171** | -0.169** |
| | [0.081] | [0.080] |
| log_NatPremsitadj | -0.127 | -0.126 |
| | [0.138] | [0.138] |
| age | -0.017 | -0.017 |
| | [0.013] | [0.013] |

| | | |
|---|---|---|
| surplus | 0.000 | 0.000 |
| | [0.000] | [0.000] |
| reinsurance | 0.003 | 0.005 |
| | [0.120] | [0.119] |
| Constant | 4.094 | 4.068 |
| | [2.642] | [2.638] |
| | | |
| Observations | 315,182 | 315,182 |
| R-squared | 0.000 | 0.000 |
| Number of panelvar | 41,678 | 41,678 |
| Insurer FE | YES | YES |
| Year FE | YES | YES |
| Adj. R-squared | 9.34e-05 | 0.000193 |
| F value | . | . |
| d.f. | 44 | 44 |

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1