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Pricing of Catastrophe Risk and the Implied Volatility Smile

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Abstract

Property-casualty (P&C) insurers are exposed to rare but severe natural disasters. This paper analyzes the relation between catastrophe risk and the implied volatility smile of insurance stock options. We find that the slope is significantly steeper compared to non-financials and other financial institutions. We show that this effect has increased over time, suggesting a higher risk compensation for catastrophic events. We are able to link the insurance-specific tail risk component derived from options with the risk spread from catastrophe bonds. Our results provide an accurate, high-frequency calculation for catastrophe risk linking the traditional derivatives market with insurance-linked securities (ILS).

Key words: Implied volatility · Options · Catastrophe risk · Tail risk · Natural disasters
JEL Classification: G12 · G13 · G14 · G22

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"The hurricane does not know the rate that was charged for the hurricane policy, so it's not going to respond to how much you charge. And if you charge an inadequate premium, you will get creamed over time."

-Warren Buffett-
June 9th 2014, Las Vegas

1 Introduction

Options allow us to evaluate the expectation of market participants regarding extreme events (Backus, Chernov, and Martin (2011)). Since property-casualty (P&C) insurance companies are exposed to natural and man-made catastrophes, options written on P&C insurance stocks should exhibit a catastrophe risk premium in the tail of their density function. This risk premium should be in excess of the tail risk in stock prices induced by market events, given that P&C insurance companies are also exposed to the overall economic development and thus the same market events. This paper analyzes the slope of the implied volatility, i.e., the absolute difference between out-of-the-money (OTM) and in-the-money (ITM) put options, as a measure of tail risk to identify a catastrophe risk premium. The idea behind this approach is that OTM options provide more effective protection against rare events than ITM options (Kelly, Pástor, and Veronesi (2015)).

There are at least three motivating aspects in analyzing tail risk specifically using options on P&C insurance stocks to identify inherent catastrophe risk.[1] First of all, catastrophes can cause great damage to specific regions. Risk-averse households are interested in offloading such risks but face high insurance premiums for this type of risk (see Froot (2001) and Zanjani (2002)). Any insight into catastrophe risk can thus further enhance our understanding of risk-adequate compensation for this type of risk. Second, some market participants specifically securitize part of their tail risk (i.e., catastrophe risk) in financial markets by means of insurance-linked securities (ILS).[2] This allows us to verify our results for catastrophe risk in another market and establish a link between the two. Third, P&C insurers use risk mitigation

[1] We define catastrophe risk as a specific and independent component of the overall tail risk to which companies are exposed. Thus, catastrophe risk is one of many potential sources of distress to a firm (here the P&C insurer). We follow Froot's (2001) definition of catastrophe risk itself, which relates to all events linked to natural hazard (e.g., hurricanes, earthquakes, wind and ice storms, floods, etc.) causing financial losses.

[2] The banking sector has also begun to apply a similar technique using contingent convertible (coco) bonds in the wake of the financial crisis. However, catastrophe bonds have already attracted investors at the end of the 1990s and, more importantly, catastrophe risk is (in general) uncorrelated with the market (Froot et al. (1995) and Zanjani (2002)), whereas coco bonds are most likely to be triggered when the rest of the economy suffers a simultaneous downturn. Thus, from an investor's perspective, the identification of catastrophe risk can be interesting for diversification purposes. In our research design, this means we have an independent component of tail risk.

techniques to reduce tail risk exposure, especially excess-of-loss reinsurance. This provides an opportunity to test whether the implied volatility slope reflects differences in the amount of risk mitigation.

No previous studies on options written on insurance stocks exist. However, the finance literature focuses on two aspects closely related to ours. First, the determinants of the implied volatility smile are important to explain the anomaly of the implied volatility smile itself (Dennis and Mayhew (2002); Bollen and Whaley (2004)). Second, the relation between the implied volatility smile and tail risk has recently gained much attention with regard to financial guarantees (Kelly, Lustig, and Nieuwerburgh (2015)) and political uncertainty (Kelly, Pástor, and Veronesi (2015)). Our paper adds an important perspective to the discussion between tail risk and the implied volatility smile by linking catastrophe risk with the steepness of the implied volatility smile.

The contribution of this paper is fourfold. First, we derive an option pricing model unique to P&C insurers which accounts for catastrophe risk and uses the derivatives market for accurate pricing of catastrophe risk. Due to the limited understanding of catastrophe risk in combination with pricing, new methods to comprehend this risk in greater detail can reduce market imperfections. Second, fair pricing for catastrophe reinsurance can affect the capital requirements for catastrophe risk and thus reduce the cost of capital (Zanjani (2002)). Third, we further enhance the reasoning with regard to the implied volatility smile. That is, we address why there is an implied volatility smile and why it is shaped the way it is (Dennis and Mayhew (2002)). Fourth, we create a link between the traditional derivatives market and ILS. From an investor's perspective, this link might be an indicator for potential arbitrage opportunities if expectations on catastrophe risk in the two markets significantly diverge.

The first finding of this paper is the identification of a catastrophe risk premium in the implied volatility smile. The implied volatility of OTM put options written on P&C insurers is 120 basis points higher than OTM put options on matched non-financials with identical historical volatility. The second finding is a strong correlation between the extracted catastrophe risk premium from option markets and the risk spreads from catastrophe bonds with expected loss and default risk being significant drivers of this result. The third finding is that catastrophe risk in derivatives has increased over time, that is, the implied volatility smile became steeper over time in comparison to options written on the rest of the market. The fourth finding is a steepening implied volatility smile around hurricane events on the day of the landfall and the days following. This suggests that market participants are more likely to protect themselves against natural catastrophes the more information about such an event arrives.

The remainder of this paper is organized as follows. Section 2 gives a brief literature review. Section 3 derives the option pricing model for P&C insurers and the corresponding hypotheses. Section 4 provides a description of the methodology and Section 5 a description of the data. Section 6 shows the empirical results. Section 7 checks for robustness and Section 8 concludes.

2 Literature

No previous studies on insurance options exist, yet there are two strands of literature relevant to this paper. The first one deals with the general findings from the finance literature regarding the determinants of the implied volatility smile and its relation to tail risk. The second strand of literature refers to the findings on insurance-specific catastrophe risk.[3]

Regarding the determinants of the implied volatility slope, Dennis and Mayhew (2002) identify several factors including beta, size, trading volume, the slope of the market index, and the volatility environment. Effects regarding the leverage effect are ambiguous, however. While Toft and Prucyk (1997) find that highly leveraged firms have steeper slopes than less leveraged firms, Dennis and Mayhew (2002) find no robust effect regarding leverage. As highlighted by Dennis and Mayhew (2002), leverage is unlikely to be a driving factor of the implied volatility smile, because currency options that cannot be subject to the leverage hypothesis also display an implied volatility smile. Also, Bakshi, Kapadia, and Madan (2003) find that index volatility smiles have a steeper slope than individual stock option smiles. Again, they empirically show that the volatility smile is not the result of the leverage effect, as assumed by Toft and Prucyk (1997). Bollen and Whaley (2004) find that the volatility smile is the result of demand pressure from public order flow. That is, the more investors ask for OTM put options on indices and OTM call options on individual stocks, the more expensive they get. Furthermore, Kelly, Lustig, and Nieuwerburgh (2015) identify cheaper prices for OTM put options on a financial sector index during the financial crisis than the sum of its individual constituents. This means that the financial sector received a government guarantee against the tail risk of plummeting stock prices and default. Another study by Kelly, Pástor, and Veronesi (2015) indicates that options in weak economies or politically uncertain countries are more valuable and contain a risk premium to protect against the tail risk of political events. Table 1 summarizes

[3]From a broader perspective, this paper is also related to the real effects of risk management on financial instruments, most notably Pérez-González and Yun (2013) who analyze weather derivatives as a risk mitigation instrument for energy companies.

the determinants and other special risk characteristics affecting the slope of the implied volatility and classifies this paper in the literature.

Table 1: Factors affecting the implied volatility smile

Factors	Effect on implied volatility smile	Source
All options		
Beta	Steeper for stocks with larger betas.	Dennis and Mayhew (2002)
Size (market cap)	Steeper for large firms.	Dennis and Mayhew (2002)
Volume	More positive for stocks with higher trading volume.	Dennis and Mayhew (2002)
Net Buying Pressure	Steeper for options which have a higher demand in contrast to those with lower demand.	Bollen and Whaley (2004)
Leverage	Ambiguous results: Toft and Prucyk (1997) find that highly leveraged firms have steeper slopes than less leveraged firms. Dennis and Mayhew (2002) find no robust effect regarding leverage.	Toft and Prucyk (1997); Dennis and Mayhew (2002)
Market Index	Steeper for individual options when market index options have steeper slope.	Dennis and Mayhew (2002)
Volatility Environment	Steeper during times of high volatility.	Dennis and Mayhew (2002)
Structure (Index vs. individual stock options)	Index volatility smiles have steeper slope than individual stock option smiles.	Bakshi, Kapadia, and Madan (2003)
Specific options		
Financial Guarantees	OTM put options on a financial sector index were cheaper during the financial crisis than the sum of its individual constituents, demonstrating an implicit insurance in the financial sector against default.	Kelly, Lustig, Nieuwerburgh (2015)
Political Risk	Options in weak economies and politically uncertain countries are more valuable, including protection against tail risk.	Kelly, Pástor, and Veronesi (2015)
Catastrophe Risk	**OTM Options of property-casualty insurers contain a risk premium for catastrophic events in excess of the market-wide tail risk.**	**This paper**

Regarding the second strand of literature (insurance-specific catastrophe findings), Thomann (2013) analyzes the relation between natural catastrophes, the 9/11 terrorist attacks, and the volatility of insurance stocks. He finds that natural catastrophes increase the volatility of insurance stocks but reduce the correlation of insurance stocks with the market. Blau, Ness, and Wade (2008); Ewing, Hein, and Kruse (2006); and Lamb (1995, 1998) find that insurer stock prices start declining in the week before landfall of a potential catastrophe in the cases of Hurricanes Katrina, Floyd, and Andrew. Interestingly, Blau, Ness, and Wade (2008) do not find significant short-selling activity prior to Katrina's landfall but during three trading days after the landfall. From a general perspective, researchers observe that investors are crash-averse and thus receive a premium in returns or insure themselves through OTM index options (see Jackwerth and Rubinstein (1996), Ait-Sahalia and Lo (2000), and Garleanu, Pedersen, and Poteshman (2009)).

Froot (2001) investigates the importance of fair pricing of catastrophe risk and the reduction of market imperfections and shows that high catastrophe risk premiums can be attributed to supply restrictions, capital market imperfections, and the market power exerted by traditional reinsurers. Furthermore, Zanjani (2002) shows that capital costs have a significant effect on catastrophe insurance markets because of high marginal capital requirements. Depending on the pricing of catastrophe insurance, these capital costs can be reduced if catastrophe risk is priced accurately.

3 Model framework and hypotheses

The main idea explored throughout this paper is that catastrophe risk is priced in OTM stock options. Catastrophe risk has to be compensated in addition to the tail risk of the overall economy and can occur either as man-made catastrophes or natural catastrophes. A candidate to investigate the relationship between catastrophe risk and the implied volatility function are options written on P&C insurance stocks, which insure the economy against large losses as a result of natural or man-made catastrophes. To answer the question about catastrophe risk being priced in stock options, we approach the issue from three different angles.

First, if catastrophe risk is an additional pricing component in deep OTM options of P&C insurers, then their slope should be steeper than for options on all other stocks. We thus compare the implied volatility function of options written on P&C insurers with the implied volatility function of options written on non-financial stocks.[4] Second, if investors and market makers anticipate catastrophes during the development of hurricanes and tropical storms and want to be insured against large losses after landfall, the difference between the slope of P&C insurance options and non-financials options should increase. Hence, we expect tail risk to increase at the arrival of new information on catastrophes. Third, if options on insurance stocks indeed capture the risk of natural disasters, their slope should be highly correlated with the catastrophe risk premium, which can be observed in catastrophe bonds. Thus, options of P&C stocks can be a high frequency, risk-neutral proxy for catastrophe risk.[5]

To formalize our assumptions and to provide us with more insight about the effects of catastrophe risk, we derive an option pricing model which accounts for an independent catastrophe risk component. For that purpose we adapt the jump-diffusion model by Martzoukos and Trigeorgis (2002). In contrast to Martzoukos and Trigeorgis (2002), we extend the model for financial and catastrophic shocks, provide economic intuition on the model, and further investigate the model's reaction along moneyness.[6]

For the non-financials stock and its single exposure to economic jump events, the model collapses to the jump-diffusion model by Merton (1976). We start with a stock, V, from the non-financial sector, which follows the continuous-time stochastic process:

$$\frac{\mathrm{d}V}{V} = \mu \mathrm{d}t + \sigma \mathrm{d}W^{(V)} + k_{econ} \mathrm{d}q_{econ}, \tag{1}$$

where μ is the drift of the underlying and σ is the volatility. $\mathrm{d}W^{(V)}$ is an increment to a standard

[4]We exclude all financial stocks from the control group for several reasons. One reason is the potential ties between the banking and insurance sector, such as bancassurance, which diffuse catastrophe risk throughout the financial system. Another reason, and closely related to the previous one, is the spillover effects identified between financial institutions, especially during volatile times (Adams, Füss, and Gropp (2014)). The last point involves effects on options written on financial institutions. Kelly, Lustig, and Nieuwerburgh (2015) document a government guarantee in OTM index options written on large financial institutions which could bias our results. Note, however, that if this government guarantee exists in individual options in a similar fashion, it would in fact decrease the implied volatility in OTM options and result in even larger discrepancies in the implied volatility slope between P&C insurers and all other stocks. In robustness tests we also include all other financial institutions to account for such potential effects (see Section 7.1).

[5]Since, in general, catastrophe bonds exclude man-made disasters (i.e., terrorism attacks or oil spills) but insurance companies write insurance for such occasions, the correlation between the slope from options on insurance stocks and the premium inherent in catastrophe bonds should not fully coincide. Furthermore, the recent entrance of large institutional investors (i.e. pension funds) in the catastrophe bond market resulted in decreasing yields for such instruments. Thus, a question that remains to be asked is whether catastrophe bonds still adequately compensate for the risk investors are bearing. Our approach might therefore be a method to indicate prices of catastrophe bonds in the absence of man-made disasters.

[6]From a theoretical perspective, the model we propose, applies to all catastrophic events – both man-made and natural. Within the category of natural catastrophes, the model is both suitable for events that "announce" themselves, such as hurricanes, and for sudden events, such as earthquakes. The reason for the suitability is the instantaneous adaptability of all parameters at the arrival of new information. From an empirical perspective, however, the model (more precisely, the difference between models) might be challenged by the fact that both P&C insurance stocks and all other stocks react evenhandedly to man-made disasters (i.e., terrorist attacks). Also empirically difficult to prove is the model's prediction for earthquakes, as there has not been a substantial earthquake in the U.S. during the sample period.

Brownian motion, and k_{econ} is the jump size caused by an economic shock, i.e., an exogenous shock, affecting the entire economy. $\mathrm{d}q_{econ}$ counts the number of economically related jumps with intensity λ_{econ} of a Poisson process.

Another stock, S, from the P&C insurance industry follows the continuous-time stochastic process:

$$\frac{\mathrm{d}S}{S} = \mu \mathrm{d}t + \sigma \mathrm{d}W^{(S)} + k_{econ}\mathrm{d}q_{econ} + k_{cat}\mathrm{d}q_{cat} \tag{2}$$

We assume that the P&C insurance stock follows the same process as the non-financials stock with identical drift and volatility except for an independent Brownian motion, $\mathrm{d}W^{(S)}$, and an additional jump component, $k_{cat}\mathrm{d}q_{cat}$. Specifically, the P&C stock is both affected by economic shocks such as the non-financials stock and additionally exposed to jumps caused by catastrophic events with jump size k_{cat} and the jump counter $\mathrm{d}q_{cat}$ with intensity λ_{cat} of a Poisson process. Note that the two Poisson processes related to economic events and catastrophic events are independent from each other. Furthermore, the risk neutral drift is defined as $r - \delta^*$, where r is the riskless rate and δ^* is defined, in the case of a P&C stock, as:

$$\delta^* \equiv \delta + \lambda_{econ}\bar{k}_{econ} + \lambda_{cat}\bar{k}_{cat}. \tag{3}$$

As such, δ^* accounts for the dividend yield, δ, and the jump effects, $\lambda_{econ}\bar{k}_{econ}$ and $\lambda_{cat}\bar{k}_{cat}$, caused by economic and catastrophic events. For the non-financials stock, the risk-neutral drift obviously excludes the jump component related to catastrophic events. In integral form, the P&C insurance stock is thus defined as:

$$\begin{aligned}\ln[S(T)] - \ln[S(0)] = \int_0^T [r - \delta^* - 0.5\sigma^2]\,\mathrm{d}t + \int_0^T \sigma \mathrm{d}W^{(S)}(t) + \sum_{q=1}^{n_{econ}} \ln(1 + k_{econ,q}) + \\ \sum_{q=1}^{n_{cat}} \ln(1 + k_{cat,q}),\end{aligned} \tag{4}$$

with n_{econ} indicating the number of economic jump events and n_{cat} indicating the number of catastrophic jump events. Again, the model assumes that the term $\sum_{q=1}^{n_{cat}} \ln(1 + k_{cat,q})$ is only present in P&C insurance stocks but not in non-financials stocks. We also assume that the jump size of an economic shock, $1 + k_{econ}$, and a catastrophic event, $1 + k_{cat}$, are log-normally distributed with:

$$\ln(1 + k_{econ}) \sim \mathbf{N}(\gamma_{econ} - 0.5\sigma^2_{econ}, \sigma^2_{econ}) \tag{5}$$

and

$$\ln(1 + k_{cat}) \sim \mathbf{N}(\gamma_{cat} - 0.5\sigma^2_{cat}, \sigma^2_{cat}) \tag{6}$$

where $\mathbf{N}(.,.)$ denotes the normal density function with mean $\gamma_{econ} - 0.5\sigma^2_{econ}$ for economically related events and $\gamma_{cat} - 0.5\sigma^2_{cat}$ for catastrophically related events. The variance of the jump size is defined as σ^2_{econ} and σ^2_{cat}, respectively. The expected value of the economic jump size is

$$E[k_{econ}] \equiv \bar{k}_{econ} = exp(\gamma_{econ}) - 1, \tag{7}$$

and the expected value of the catastrophic jump size is

$$E[k_{cat}] \equiv \bar{k}_{cat} = exp(\gamma_{cat}) - 1. \tag{8}$$

For the model development, it is important to highlight the difference between the jump size means of economic and catastrophic events. While economic shocks can be positive or negative with potentially equal probability (e.g., higher or lower than expected economic growth, central bank interventions, new technologies, economic crises, bailouts, etc.), catastrophic events are *on average* negative, with either a negative impact (i.e., catastrophe occurs) or no impact (i.e., catastrophe does not occur) but theoretically not a positive impact. In other words, a P&C insurer has already collected all premiums at the beginning of the year. These funds can only decrease in value through the occurrence of catastrophic events. Hence, there is no upside but only a downside to the earnings.[7] Under this assumption, the expected jump size of catastrophic shocks should be more negative than the expected jump size of economic shocks (i.e., $\gamma_{cat} < \gamma_{econ}$). We can then define the value of a European put option on a P&C insurance stock as:

$$F_{Put}(S, X, T, \sigma, \delta, r, \lambda_i, \gamma_i, \sigma_i) = e^{-rT} \sum_{n_{econ}=0}^{\infty} \sum_{n_{cat}=0}^{\infty} \{P(n_{econ}, n_{cat}) \times E[(X - S_T)^+ | (n_{econ}, n_{cat}) jumps]\} \tag{9}$$

where X is the strike price of the put option and $P(n_{econ}, n_{cat})$ describes the joint probabilities of economic and catastrophic shocks on a P&C insurer. Because the probabilities for catastrophic and

[7] We acknowledge that this is a simplified perspective, given that other factors play an important role, too, such as reinsurance cover or the safety loadings in insurance prices. However, on average, this assumption should hold if insurance prices are fair.

economic jumps are assumed to be independent, this term is defined as:

$$P = (n_{econ}, n_{cat}) = \frac{e^{(-\lambda_{econ}-\lambda_{cat})T}(\lambda_{econ}T)^{n_{econ}}(\lambda_{cat}T)^{n_{cat}}}{n_{econ}!n_{cat}!} \tag{10}$$

Based on Martzoukos and Trigeorgis (2002) and the Black-Scholes model, we can derive the risk-neutral expectation $E[(X - S_T)^+|(n_{econ}, n_{cat})jumps]$ of a put option written on a P&C insurance stock which is subject to jumps caused by the overall economy and by catastrophic events, as follows:

$$E[(X - S_T)^+|(n_{econ}, n_{cat})jumps] = XN(-d_{2n}) - Se^{[(r-\delta^*)T+(n_{econ}\gamma_{econ})+(n_{cat}\gamma_{cat})]}N(-d_{1n}) \tag{11}$$

where d_{1n} is defined as:

$$d_{1n} \equiv \frac{\ln(S/X) + (r-\delta^*)T + (n_{econ}\gamma_{econ}) + (n_{cat}\gamma_{cat}) + 0.5\sigma^2 T + 0.5n_{econ}\sigma^2_{econ} + 0.5n_{cat}\sigma^2_{cat}}{\sqrt{\sigma^2 T + n_{econ}\sigma^2_{econ} + n_{cat}\sigma^2_{cat}}}, \tag{12}$$

and d_{2n} is defined as:

$$d_{2n} \equiv d_{1n} - \sqrt{\sigma^2 T + n_{econ}\sigma^2_{econ} + n_{cat}\sigma^2_{cat}} \tag{13}$$

Having defined the model, we can calibrate it and use it to guide the empirical analyses. Because no previous empirical analysis on options written on insurance stocks exists, we do not have a strong prior on the effect of catastrophes on these instruments. However, as mentioned before, we reckon that the mean jump size for catastrophes is more negative than for economic shocks. Aside from reasonable values for the non-financials stock which follows the calibration by Martzoukos and Trigeorgis (2002), our only condition is that $\gamma_{cat} < \gamma_{econ}$. For simplicity, we assume identical standard deviations of the jumps, i.e. ($\sigma_{cat} = \sigma_{econ}$). The following Table 2 summarizes our calibration values.

Table 2: Option model calibration

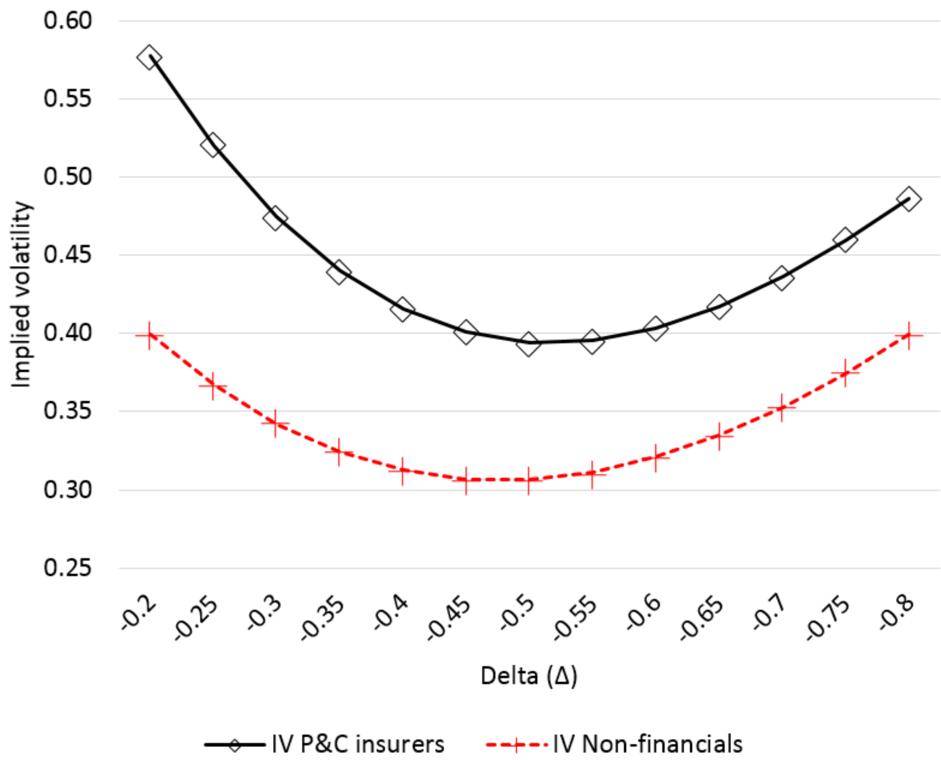
P&C insurance stock		Non-financials stock	
$S =$	100	$V =$	100
$\sigma =$	0.20	$\sigma =$	0.20
$r =$	0.02	$r =$	0.02
$\delta =$	0.03	$\delta =$	0.03
$T =$	0.083	$T =$	0.083
$\gamma_{econ} =$	-0.02	$\gamma_{econ} =$	-0.02
$\sigma_{econ} =$	0.50	$\sigma_{econ} =$	0.50
$\lambda_{econ} =$	1.00	$\lambda_{econ} =$	1.00
$\gamma_{cat} =$	-0.10		
$\sigma_{cat} =$	0.50		
$\lambda_{cat} =$	1.00		

This table presents the parameters used to calibrate the model for a representative option written on a P&C insurance stock and a representative option written on a stock from the non-financial sector. Both instruments share the same parameters and values, except for the additional catastrophe-related parameters used in the P&C insurance stock.

As OptionMetrics reports implied volatilities on a grid of delta (Δ) values between -0.2 and -0.8, we report the model results on exactly the same grid to facilitate comparisons.[8] We compute put option prices based on the model and accordingly extract Black-Scholes implied volatilities and delta values.[9] Figure 1 shows the results from our model calibration.[10]

[8]As noted by Kelly, Pástor, and Veronesi (2015), delta is also a better measure for moneyness, as it reflects the probability of an option contract to expire in the money by considering maturity, volatility, and the risk-free rate.
[9]We use a cubic function to fit the implied volatilities on the delta grid between -0.2 and -0.8.
[10]Appendix A also illustrates model sensitivities for other calibrations of the catastrophe-related parameters.

Figure 1: Modeled implied volatility smiles (P&C insurers vs. non-financial firms)



This figure illustrates the modeled implied volatilities (IV) of one-month-to-expiration put options written on P&C insurance stocks (black line marked by squares) and non-financials stocks (red dotted line marked by crosses) along moneyness. Moneyness is expressed in delta values on the x-axis. The P&C insurance stock is calibrated with S = 100, σ = 0.20, r = 0.02, δ = 0.03, T = 0.083, γ_{econ} = -0.02, σ_{econ} = 0.50, λ_{econ} = 1.00, γ_{cat} = -0.10, σ_{cat} = 0.50, and λ_{cat} = 1.00. The non-financials stock is calibrated with V = 100, σ = 0.20, r = 0.02, δ = 0.03, T = 0.083, γ_{econ} = -0.02, σ_{econ} = 0.50, and λ_{econ} = 1.00.

Our first observation is that insurance put options are more expensive at all moneyness categories (delta values). Our second observation, which addresses the main idea of this paper, is the steeper slope of insurance put options compared to non-financials put options as a result of the additional negative catastrophe jump probability. The third observation we make in our model is that a negative increase in the mean jump size increases the steepness of the slope. This effect is more pronounced the less uncertainty about the jump prevails, σ_{cat}, and the more negative the jump size is. Motivated by the model's response to catastrophic events, we formulate our hypotheses.

Hypothesis 1: The implied volatility slope of put options written on P&C insurers is on average steeper *than the slope of put options written on non-financials.*

Because it is unknown when and where a catastrophe will occur, an additional tail risk component related to catastrophe risk should result in a steeper implied volatility smile, which is the result of higher implied volatilities of OTM put options and lower ITM implied volatilities with the jump size, γ_{cat}, and the jump uncertainty, σ_{cat}, driving this effect.

Hypothesis 2: The implied volatility slope of put options written on P&C insurers is related to the risk premium from the catastrophe bond market.

If the tail risk component is indeed related to losses caused by catastrophes, the steepness of the implied volatility smile should follow the price development of the catastrophe bond market because this market provides a price orientation for actively traded catastrophe risk. If the no-arbitrage condition holds, both markets should share a common time-series variation.

Hypothesis 3: In comparison to the slope of put options written on non-financials, the implied volatility slope of put options written on P&C insurers is steeper after a catastrophic event compared to before the event.

Because uncertainty about the jump, σ_{cat}, reduces in terms of whether and where an event occurs, and estimations about the jump size, γ_{cat}, increase in the case of realized catastrophes, the slope of the implied volatility should become even steeper after an event.

4 Methodology

We analyze the difference between OTM and ITM put options. That is, our main focus is the difference in levels of the implied volatility smile. As mentioned above, the main idea is that OTM options provide a more effective protection against rare events than ITM options (Kelly, Pástor, and Veronesi, 2015). Our slope measure follows Kelly, Pástor, and Veronesi (2015) where the slope of the implied volatility function of firm i at time t is the difference in implied volatilities between OTM puts, $IVola_{i,t}^{OTMP}$, and ITM puts, $IVola_{i,t}^{ITMP}$. Formally, the slope is defined as:

$$SLOPE_{i,t} = IVola_{i,t}^{OTMP} - IVola_{i,t}^{ITMP} \tag{14}$$

where $IVola_{i,t}^{OTMP}$ corresponds to the implied volatility of an OTM put option with a fixed delta of -0.20 and a constant time to maturity of 30 days. $IVola_{i,t}^{ITMP}$ corresponds to the implied volatility of an ITM put option with a fixed delta of -0.80 and a constant time to maturity of 30 days.[11] As noted by Bollerslev and Todorov (2011), short-maturity OTM options are worthless unless a big jump occurs before expiration, making them particularly interesting in the context of catastrophe risk. In univariate tests, we first analyze whether the slope of the implied volatility of options on insurance stocks is in fact steeper than the rest of the market, as we hypothesize. We do so by comparing the implied volatility slope of P&C insurers and non-financial firms at the end of each month.

Identical to Yan (2011), we start out using end-of-month observations in the implied volatilities to guarantee homogeneity between all options while finding a matching historical volatility in the control group (i.e., options on non-financials).[12] We then turn to weekly cross-sectional Fama-MacBeth (1973) regression as in Dennis and Mayhew (2002) to control for other variables that might influence a steeper slope in insurance stocks. Formally, the cross-sectional Fama-MacBeth (1973) regression is defined as:

$$\begin{aligned} SLOPE_{i,t} = \alpha_{i,t} + INSURANCE_{i,t} + IVATM_{i,t} + LEVERAGE_{i,t} + SIZE_{i,t} \\ + BETA_{i,t} + VOLUME_{i,t} + CALLPUTOI_{i,t} + SLOPE_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{15}$$

where $INSURANCE_{i,t}$ is the variable of interest and defined as a dummy variable taking the value of one if the slope refers to a P&C insurer and zero if it refers to a non-financials stock. If P&C insurers indeed bear a risk premium for natural catastrophes (and man-made disasters) compared to the rest of the market, this variable should be significantly positive, meaning that the difference between OTM and ITM put options is larger for P&C insurers.

Following Dennis and Mayhew (2002), the first control variable is $IVATM_{i,t}$ which is the contemporaneous weekly average of at-the-money (ATM) implied volatilities of company i at week t. We use a delta of -0.50 for an option to be ATM. If the overall level influences the slope in the cross-section,

[11] We use these parameters because the implied volatility grid provided by OptionMetrics is bounded by delta values between -0.20 and -0.80. Thus, we use the most extreme delta values available to approximate the most efficient and the least efficient way to protect against rare events.

[12] For further details, see Section 6.1.

it is necessary to control for an effect which could limit the upper bound of OTM options. We also include $LEVERAGE_{i,t}$ as a control variable. We divide the book value of total assets by the market value of equity and take the natural logarithm of the ratio to define $LEVERAGE_{i,t}$ (Kelly, Lustig, and Nieuwerburgh (2015)). We use total assets from the last fiscal year lagged by four months and contemporaneous market equity at time t. This variable might be particularly important, because P&C insurers are characterized by high leverage values. Black (1976) and Toft and Prucyk (1997) argue that leverage mechanically results in higher volatilities because, as the equity value of a levered company decreases, the leverage ratio has to increase, and thus the volatility of that company has to increase. However, results about leverage in the implied volatility context are ambiguous. For example, there are significantly steep slopes for unlevered firms and also currency options that are not exposed to leverage ratios (Dennis and Mayhew (2002)).

The third control variable is $SIZE_{i,t}$, measured as the contemporaneous natural logarithm of market equity of stock i at time t. It could be the case that smaller companies tend to be more risky (Banz (1981)) and might be more susceptible to default risk (Vassalou and Xing (2004)). Furthermore, we check for the systematic risk, $BETA_{i,t}$, of each stock, assuming that higher risk exposure should result in steeper slopes. The rolling market beta is calculated by regressing daily excess returns of stock i against CRSP's value-weighted market return in excess of the risk-free rate over the past 200 days. Another control variable is $VOLUME_{i,t}$ which is defined as the logarithm of average daily trading volume over week t. We include this variable as a proxy for liquidity (Dennis and Mayhew (2002)). More trading activity in the underlying stock implies a higher demand for options including hedges against downside movements in stock prices. The control variable $CALLPUTOI_{i,t}$ captures the trading pressure between calls and puts which could explain higher prices due to higher demand for either one of them (Dennis and Mayhew (2002); Bollen and Whaley (2004)). We determine the total open interest over the entire week for calls and puts and then divide this number by the difference between total open interest in calls and total open interest in puts over the entire week. This measure is bound between -1 and +1. A negative value indicates larger interest for put options, and a positive value indicates larger interest for call options. To capture any persistence and residual explanatory power in the implied volatility slope, we include the implied volatility slope lagged by one week, $SLOPE_{i,t-1}$.

In addition to the cross-sectional Fama-MacBeth (1973) regressions, we run pooled time-series cross-sectional regressions with clustered standard errors by firm and week to account for market-wide factors, the unbalanced panel, and the firm and time dependency (Petersen (2009)). It is well-known that volatility appears in clusters, with certain time periods being more volatile than others (Maheu and McCurdy (2004)). Thus, if some stocks are more prone to changes in volatility clustering or changes in overall market volatility than others, the slope of implied volatility could also be affected. The pooled time-series cross-sectional regression can therefore capture the time series variation in the slope of the implied volatilities and is formally defined as:

$$\begin{aligned} SLOPE_{i,t} = \alpha_{i,t} + INSURANCE_{i,t} + IVATM_{i,t} + LEVERAGE_{i,t} + SIZE_{i,t} + BETA_{i,t} \\ +VOLUME_{i,t} + CALLPUTOI_{i,t} + SLOPE500_{i,t} \\ +IVATM500_{i,t} + SLOPE_{i,t-1} + \varepsilon_{i,t}. \end{aligned} \tag{16}$$

To capture the market-wide effects, we include both the slope of the S&P500 Index ($SLOPE500_{i,t}$) and the overall level of the market volatility proxied by the implied volatility of ATM options of the S&P500 Index ($IVATM500_{i,t}$).

5 Data

We retrieve daily data on all put options from the standardized volatility surface provided by OptionMetrics between January 1996 and December 2013. The complete sample consists of 67 U.S. P&C insurers and 5596 companies from the non-financial sector.[13] OptionMetrics' volatility surface calculates an interpolated implied volatility surface using a kernel smoothing algorithm for puts and calls with different strikes and maturities. The resulting standardized grid includes delta values in steps of 0.05 from -0.20 (i.e. OTM put option) to -0.80 (i.e. ITM put options). Binomial trees are used to first compute the underlying implied volatilities, allowing for early exercise and considering expected dividends to be paid until the maturity of the options. Note that a standardized option is only documented in OptionMetrics' volatility surface if there are sufficient underlying option data on each day to accurately determine an interpolated implied volatility. The advantage of using the standardized volatility surface is that we do not have to proceed with ranges of diverging maturity or strike prices, which could ultimately introduce a measurement bias.

[13]A complete list of all 67 P&C insurers can be found in Appendix B.

To analyze catastrophe risk, we differentiate between P&C insurers with SIC code 6331 and all other options that are not financial stocks (i.e. excluding options with SIC codes between 6000 and 6999).[14] Using short-dated options with 30 days to maturity has two advantages. First, they are the most liquidly traded ones in contrast to options with longer maturities (Driessen, Maenhout, and Vilkov (2009)). Second, a natural disaster is temporarily restricted. That is, an earthquake takes only a few minutes, and a hurricane in general takes no more than two to three weeks from initial development until landfall. Thus, the actual cost after a disaster can be roughly estimated after such an event. Consequently, investors would want to be insured for the time period in which actual costs are estimated to avoid the greatest uncertainty about claim payments.[15]

Table 3: Descriptive statistics

	Panel A: P&C insurers			*Panel B: Non-Financials*		
Variable	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Obs.
$SLOPE_{i,t}$	0.058	0.116	28,290	0.034	0.111	1,947,873
$IVATM_{i,t}$	0.338	0.179	28,290	0.518	0.268	1,947,873
$LEVERAGE_{i,t}$	1.355	0.742	27,887	-0.141	1.197	1,760,953
$SIZE_{i,t}$	9.538	1.527	27,868	7.673	1.653	1,760,307
$BETA_{i,t}$	0.872	0.331	27,829	1.160	0.592	1,837,527
$VOLUME_{i,t}$	1,273,109	6,435,054	28,290	1,472,984	4,421,952	1,894,309
$CALLPUTOI_{i,t}$	0.242	0.419	28,290	0.279	0.361	1,947,873
	Panel C: Market (S&P 500)					
Variable	Mean	Std. Dev.	Obs.			
$SLOPE500_t$	0.065	0.032	936			
$IVATM500_t$	0.195	0.076	936			

This table presents the mean, standard deviation (Std. Dev.), and the number of firm-week observations of the dependent variable ($SLOPE_{i,t}$) and the explanatory variables. Panel A reports these variables for property-casualty insurers. Panel B reports these variables for the control group of stocks in the non-financials sector. Panel C reports market-wide explanatory variables based on the S&P500. The sample period starts in the first week of January 1996 and ends in the last week of December 2013.

We only use individual equity options and exclude index options (i.e., the OptionMetrics index flag equals 0). Accounting data to calculate leverage figures are retrieved from COMPUSTAT. Daily trading information regarding volume, size, and returns are from CRSP. Data on open interest and the implied

[14]We focus on P&C insurers identified by the SIC code to avoid any selection bias and also because investors might not be able to differentiate how much exposure the underlying insurer has towards catastrophe risk. This argument is based on the opacity of insurance markets and the well-protected underwriting exposure (Cummins and Weiss (2009)).

[15]Overall, this intuition is contrary to a financial crisis, which includes contagion effects and risks that can take several months or even years to be discovered.

volatility of the S&P500 are gathered from OptionMetrics. Another analysis in this paper refers to the link between the implied volatility slope and catastrophe risk. Since there is in fact a market for catastrophe risk in the form of catastrophe bonds, we can actually relate the slope of the implied volatility to actual catastrophe risk. For that purpose, we use the quarterly data of cat bond spreads from Braun (2016).[16] If both measures are related to each other, they should be highly correlated. This would not only provide evidence of what the slope is in fact measuring but also establish accurate pricing for catastrophe risk.

Table 3 summarizes the dependent and independent variables in terms of mean, standard deviation, and the number of firm-week observations. Panel A reports these variables for the treatment group of P&C insurers and Panel B for the control group of stocks in the non-financials sector. Panel C reports market-wide explanatory variables based on the S&P500.

6 Empirical analysis

The empirical analysis starts with univariate tests (Section 6.1), followed by Fama-MacBeth (1973) regressions (Section 6.2) and panel (pooled cross-sectional time-series) regressions (Section 6.3) and then establishes the link between the implied volatility slope and the catastrophe risk market (Section 6.4). The last analysis addresses the reaction of the implied volatility around catastrophic events (Section 6.5).

6.1 Implied volatility of property-casualty insurers and non-financials

To adequately compare the implied volatility of P&C insurers with the rest of the market in univariate tests we use a matching procedure based on the realized volatility of a stock. This procedure guarantees both a fair comparison of the slope and of the levels of the implied volatility *at each value of delta*.[17] Specifically, the implied volatility measures the future volatility market participants expect for a stock. Assuming there are two stocks with the same realized volatility in time t, one could expect that their future volatility is identical, too, unless market participants expect the future volatility of one stock to be higher than the rest of the market due to additional risk components. Here, we expect that investors

[16] The term "spread" relates to the yield from primary markets at initial issuance of the catastrophe bond in excess of the risk free rate. We would like to thank Alexander Braun for making the data available to us.

[17] Note that the matching procedure is not necessary for our key analysis regarding the slope that we propose, which is overall steeper for P&C insurers compared to non-financial firms. However, the overall level of OTM, ATM, and ITM implied volatilities of non-financials is higher. In the following regression analysis, we are only interested in the slope and do not compare implied volatilities at different delta values. Thus, we include all P&C insurers and non-financial firms without any matching procedure in the regression analysis. Similar matching procedures in the context of stock splits are used by Shaik (1989).

add an additional risk component in (deep) OTM put options of P&C insurers due to catastrophe risk, a risk component which should not appear in non-financials with identical realized volatility. Using data on realized volatility over the past 365 days from OptionMetrics, we match the implied volatility of insurance stocks with the implied volatility of non-financials stocks.[18] At the end of each month, we match each P&C insurance stock with a portfolio of all available non-financial stocks of identical realized volatility.[19]

Table 4: Implied volatilities for options from P&C insurers and non-financials

Panel A	*Puts on property-casualty insurance stocks*												
Δ	**-0.20**	**-0.25**	**-0.30**	**-0.35**	**-0.40**	**-0.45**	**-0.50**	**-0.55**	**-0.60**	**-0.65**	**-0.70**	**-0.75**	**-0.80**
Mean	0.407	0.384	0.368	0.357	0.348	0.342	0.337	0.333	0.331	0.33	0.333	0.339	0.348
Std. dev.	0.228	0.220	0.213	0.207	0.204	0.201	0.200	0.197	0.194	0.195	0.197	0.200	0.203
Obs.	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552	6552
Panel B	*Puts on non-financials stocks*												
Δ	**-0.20**	**-0.25**	**-0.30**	**-0.35**	**-0.40**	**-0.45**	**-0.50**	**-0.55**	**-0.60**	**-0.65**	**-0.70**	**-0.75**	**-0.80**
Mean	0.396	0.376	0.363	0.353	0.346	0.341	0.337	0.334	0.333	0.335	0.339	0.346	0.358
Std. dev.	0.165	0.164	0.163	0.162	0.162	0.161	0.160	0.160	0.160	0.160	0.161	0.163	0.166
Obs.	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546	6546

This table presents the mean and standard deviation of implied volatilities of individual equity options with one month (30 days) to expiration and fixed deltas at the end of each month during the sample period. Panel A shows the implied volatilities of all P&C insurers with SIC code 6331. Panel B shows the matched implied volatilities of non-financial firms with identical historical volatility over the past 365 days. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013.

Panel A of Table 4 shows the mean of the implied volatilities (and the standard deviation) of puts on P&C insurers stocks at different values of delta. Panel B shows the mean of the implied volatilities (and the standard deviation) of puts on non-financials stocks at different values of delta.[20] Table 5 tests the equality of the implied volatilities between P&C insurers and non-financials. As expected, the deep OTM insurance stock options are significantly higher (i.e., an implied volatility of 0.407) than those of deep OTM non-financials options. The matching procedure appears to be well specified as ATM options at a delta value of -0.50 for both categories are virtually identical (0.337 vs. 0.337 with a t-statistic for the difference of -0.10).

[18]We use 365-days historic volatility to avoid seasonal effects that might affect shorter volatility measures.

[19]Since there are more non-financial stocks than P&C insurer stocks, we average the implied volatility from non-financials options to avoid any selection bias.

[20]Note that six realized volatility observations from P&C insurers could not be matched with identical realized volatility from non-financials. For the sake of completeness, we report all implied volatilities of P&C insurers. If we exclude the six observations, results are virtually unchanged. Furthermore, the following regression analysis uses the entire universe of P&C insurers and non-financials.

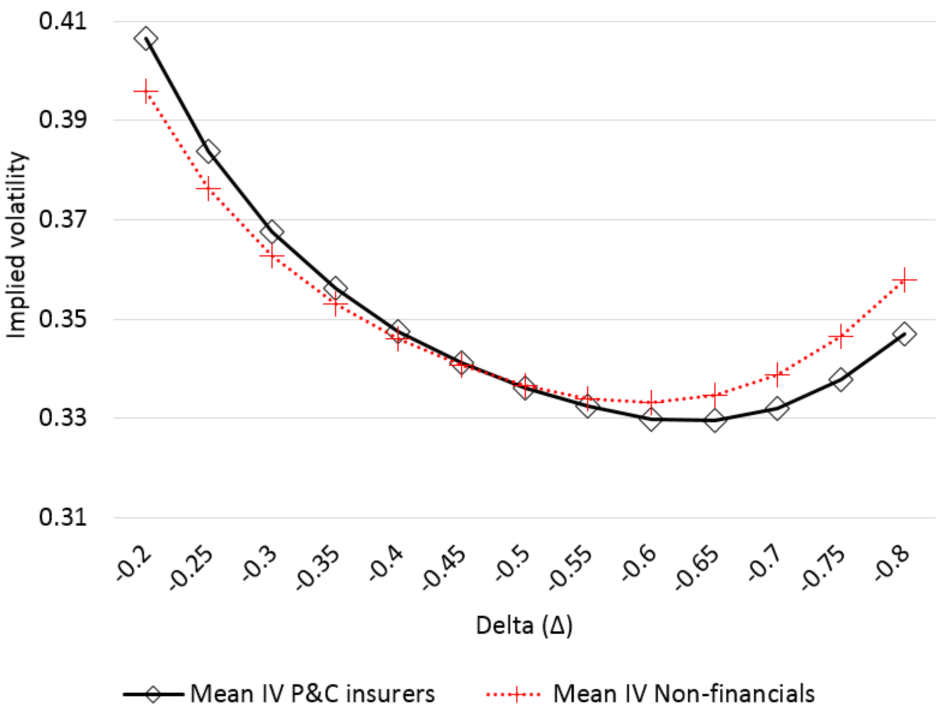
Table 5: Testing equality of implied volatilities

							Puts						
Δ	**-0.20**	**-0.25**	**-0.30**	**-0.35**	**-0.40**	**-0.45**	**-0.50**	**-0.55**	**-0.60**	**-0.65**	**-0.70**	**-0.75**	**-0.80**
Mean P&C	0.407	0.384	0.368	0.356	0.348	0.341	0.336	0.333	0.330	0.329	0.332	0.338	0.347
Mean non-financials	0.396	0.376	0.363	0.353	0.346	0.341	0.337	0.334	0.333	0.335	0.339	0.346	0.358
Difference (Mean)	0.011***	0.007**	0.005	0.003	0.002	0.000	0.000	-0.002	-0.004	-0.005*	-0.007**	-0.009***	-0.011***
t-statistic	[3.11]	[2.21]	[1.49]	[0.99]	[0.49]	[0.14]	[-0.10]	[-0.48]	[-1.14]	[-1.68]	[-2.15]	[-2.69]	[-3.37]
Difference (Median)	-0.004***	-0.004***	-0.002***	-0.004***	-0.003***	-0.005***	-0.005***	-0.006***	-0.007***	-0.009***	-0.012***	-0.014***	-0.019***
Wilcoxon-z	[-3.68]	[-3.90]	[-3.97]	[-3.98]	[-4.02]	[-4.26]	[-4.61]	[-4.89]	[-5.57]	[-6.57]	[-7.57]	[-8.74]	[-10.01]
Hist. volatility							0.323						
Obs.							6546						

This table reports the means of implied volatilities of options written on property-casualty insurers and non-financial firms. Time to expiration of the individual equity options is one month (30 days). Each implied volatility corresponds to a fixed delta value (Δ). Implied volatilities of the non-financial control group are matched with implied volatilities of P&C insurers based on identical historical volatility over the past 365 days. The table also reports the difference of the means (Difference (Mean)) for each delta category with T-statistics reported in brackets below the mean values. The difference in medians (Difference (Median)) is shown below with z-statistics of the Wilcoxon–Mann–Whitney rank-sum test in brackets. The average realized volatility for all stocks over the entire sample is 0.323. Six non-matched implied volatilities from the P&C sample are excluded. Each sample thus consists of 6,546 observations. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

In contrast, deep ITM put options for non-financials have significantly higher implied volatilities than P&C insurers. This suggests that investors and market makers are indeed more worried about severe declines in P&C stock prices for which they want to be insured against but not about smaller movement where deep ITM options can be useful.[21] This relation between delta and implied volatilities is also illustrated in Figure 2.

Figure 2: Implied volatility smiles of traded put options (property-casualty insurers vs. non-financial firms)



This figure illustrates the implied volatilities of one-month-to-expiration put options of property-casualty insurance stocks (black line marked by squares) and non-financials stocks (red dotted line marked by crosses) derived from traded put options along moneyness. Moneyness is expressed in delta values on the x-axis. The matched sample consists of non-financial stocks and property-casualty insurance stocks based on 365-day realized volatility. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013.

[21] We also run non-parametric tests presented in Table 5 using the Wilcoxon–Mann–Whitney rank-sum test. In this setting, median implied volatilities of P&C insurers are not higher than the implied volatilities of non-financials. However, the median difference becomes smaller the more out-of-the-money the option gets. There might be several reasons for that including stronger effects in the post-Katrina period and peak events (i.e., hurricanes) which further increase the slope during specific time periods. These reasons explain to some extent the discrepancy between the mean and the median difference in implied volatilities.

We can see that the shape of the implied volatility smile of P&C insurers from actual data follows closely the shape described by the option pricing model and also exhibits a steeper slope than non-financials.[22] However, the shape and level of the implied volatility smile of non-financials is much closer and steeper to the P&C insurers. An explanation for such a pattern is that non-financials are exposed to other tail risk components which are, however, not as extreme as catastrophes for P&C insurers.[23] This would explain the similar level in implied volatilities of put options written on P&C insurers and non-financials and at the same time account for the steeper slope of non-financials.

With the discovery of a significantly positive difference between P&C insurers and non-financials in OTM put options but none between ATM put options and a significantly negative one between ITM put options, the question remains whether this difference also results in a statistically significant slope difference between the two groups. We compute the slope as defined in Section 4 for both P&C insurers and non-financials.

Table 6: Univariate comparison of the slope of the implied volatilities (property-casualty insurers vs. non-financial firms)

	P&C insurers	Non-financials	*Unpaired two-sided t-test* Mean	*Wilcoxon test* Median
$IVOLA_{i,t}^{OTMP}$	0.407	0.396		
$IVOLA_{i,t}^{ITMP}$	0.347	0.358		
$SLOPE_{i,t}$	0.060	0.038	0.022***	0.004***
			[9.50]	[7.11]
Obs.	6546	6546		

This table reports the mean of implied volatilities of out-of-the-money (OTM) and in-the-money (ITM) put options written on property-casualty insurers and non-financial firms. The slope of property-casualty insurers and non-financials is defined as the difference between OTM (delta = -0.20) and ITM (delta = -0.80) put options. The table also compares the means between the slopes of property-casualty insurers and non-financials using an unpaired two-sided t-test as well as their medians based on the Wilcoxon–Mann–Whitney rank-sum test. Time to expiration of the individual equity options is one month. Implied volatilities of the non-financial comparison group are matched with implied volatilities of property-casualty insurers based on 365 days of realized volatility. The average realized volatility for all stocks over the entire sample is 0.323. Realized and implied volatilities are retrieved from OptionMetrics. The sample period is January 1996 to December 2013. T-statistics and z-statistics are reported in brackets, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

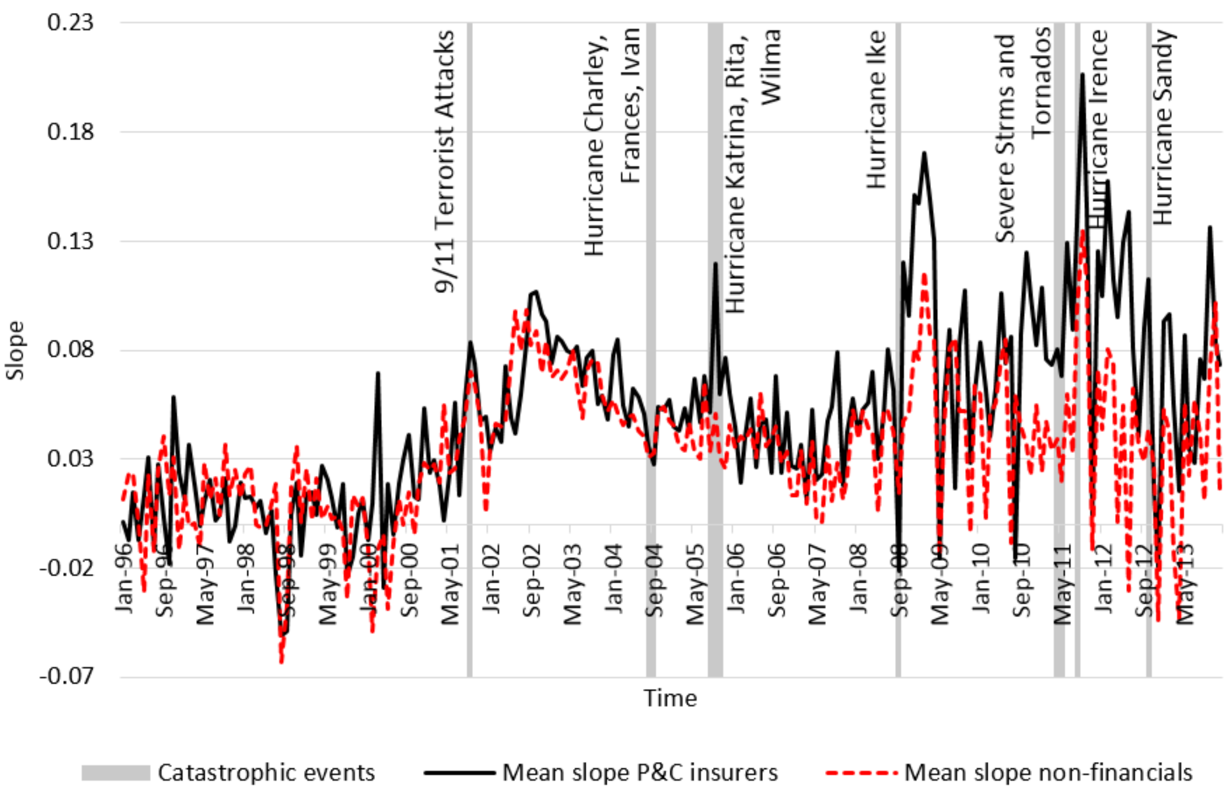
[22] Although we are interested in the shape of the implied volatility, it should be mentioned that the levels are overestimated by the model which is mainly attributable to an extensive λ_{cat} and σ_{cat}, and thus represent a calibration issue.

[23] Each company could be exposed to an industry-specific tail risk component. For example, a pharmaceutical could be sued for a flawed drug, or an automotive company could be forced to recall their vehicles because of defective brakes.

Table 6 shows that the parametric and the non-parametric difference between both slopes is highly significant, meaning that investors expect a higher probability of tail risk for P&C insurers, although historical volatility would not imply such a difference.

Beyond the time-series averages of the implied-volatilities for P&C insurers and non-financials, it might be of interest how the two groups develop over time. We thus graph the slope of the implied volatility for both categories separately in Figure 3. An interesting observation we make here is that the slope of P&C insurers was identical and even slightly below the slope of non-financials during the time until Hurricane Katrina in 2005.

Figure 3: Slope of the implied volatility smile of P&C insurers and non-financials over time



This figure illustrates the slope of the implied volatility smile from options written on property-casualty insurers (black solid line) and non-financials (red dotted line) over time, with identical 365-days historical volatility. The sample period is January 1996 to December 2013.

Since Hurricane Katrina, however, it appears that P&C insurers were mostly above the slope of non-financials, suggesting that a change in perception among market participants occurred regarding large losses insurers are exposed to.

6.2 Fama-Macbeth (1973) regressions

We now turn to the multivariate analysis of the slope, including all equity options on P&C insurers and non-financials. Table 7 reports the results of the cross-sectional regression analysis with the slope (as defined in Section 4) as the dependent variable. When we only include the dummy variable $INSURANCE_{i,t}$ in our regression (Column I), we find similar results for the difference in slopes as in Table 6, both in terms of economic and statistical significance. Note that the dependent variable includes all slopes of P&C insurers and non-financials. Column II includes the control variables presented in Section 4. The economic and statistical difference of $INSURANCE_{i,t}$ remains highly significant at the 1%-level.

Table 7: Fama-MacBeth (1973) regressions

	(I)	(II)	(III)
$INSURANCE_{i,t}$	0.016***	0.015***	0.005***
	[7.47]	[6.59]	[6.37]
$IVATM_{i,t}$		-0.043***	-0.031**
		[-10.03]	[-2.44]
$LEVERAGE_{i,t}$		-0.003***	-0.004
		[-2.95]	[-1.25]
$SIZE_{i,t}$		-0.001	-0.002
		[-0.99]	[-1.35]
$BETA_{i,t}$		0.007***	0.002**
		[6.68]	[2.04]
$VOLUME_{i,t}$		-0.000	0.000
		[-1.10]	[0.97]
$CALLPUTOI_{i,t}$		-0.001	0.000
		[-0.64]	[0.45]
$SLOPE_{i,t-1}$			0.649***
			[50.03]
Intercept	0.032***	0.053***	0.037**
	[15.11]	[6.48]	[2.29]
Avg. R^2	0.00	0.04	0.46
Weeks	936	928	928
Obs.	1,976,163	1,736,945	1,733,939

This table reports Fama-MacBeth (1973) regressions with the slope of the implied volatility smile as dependent variable. The sample period is January 1996 to December 2013. T-statistics are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. Avg. R^2 is the time-series average R-square from each weekly cross-sectional regression. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We also include the previous week implied volatility slope (Column III) to capture any omitted factors. The implied volatility slope of the previous week is highly significant, which suggests that the slope is very persistent and thus predicable over time (see An et al. (2014)). The variable $INSURANCE_{i,t}$, though, remains statistically and economically significant at the 1%-level.

Overall, the results show that fundamental and option-related data cannot explain the steeper slope of options written on P&C insurers. Rather, they are specifically exposed to extreme catastrophe events which investors and market markers acknowledge with higher OTM put option prices (and lower ITM put option prices) compared to options on non-financials.

6.3 Panel regression

While the Fama-MacBeth (1973) regressions indicate significant relationships between the slope insurance-specific catastrophe risk, they do not allow us to check time-dependent effects. Specifically, volatility in general is found to cluster. That is, some periods in time show stronger volatility patterns, while other periods are less volatile. If some options are more prone to changes in volatility clustering or changes in overall market volatility compared to others, the slope of implied volatility could also be affected. The pooled time-series cross-sectional regression can therefore capture the time series variation in the slope of the implied volatilities. Table 8 shows the results of the panel regression. Again, $INSURANCE_{i,t}$ is highly significant in all settings. Indeed, the level of the market volatility proxied by the implied volatility of ATM S&P500 Index put option captures some of the time-series variation of the slope of the implied volatility. The slope of S&P500 Index put options, however, is insignificant and appears to have no impact on the slope of individual equity options as soon as the past slope of the individual stock is included in the regression setting.

Table 8: Panel regression with cross-sectional and time-series clustered standard errors

	(I)	(II)	(III)	(IV)
$INSURANCE_{i,t}$	0.024***	0.023***	0.023***	0.008***
	[5.56]	[5.05]	[5.13]	[4.98]
$IVATM_{i,t}$		-0.026***	-0.046***	-0.016***
		[-6.25]	[-11.18]	[-9.16]
$LEVERAGE_{i,t}$		-0.000	-0.001	-0.000*
		[-0.32]	[-1.60]	[-1.88]
$SIZE_{i,t}$		-0.001	-0.002***	-0.001***
		[-1.46]	[-4.04]	[-3.05]
$BETA_{i,t}$		0.009***	0.012***	0.004***
		[10.01]	[13.94]	[10.62]
$VOLUME_{i,t}$		-0.000	-0.000	-0.000
		[-0.40]	[-0.12]	[-1.52]
$CALLPUTOI_{i,t}$		-0.008***	-0.007***	-0.002***
		[-6.00]	[-5.86]	[-4.52]
$SLOPE500_{i,t}$			-0.197***	-0.032
			[-4.73]	[-1.21]
$IVATM500_{i,t}$			0.179***	0.051***
			[9.77]	[4.31]
$SLOPE_{i,t-1}$				0.664***
				[122.02]
Intercept	0.034***	0.045***	0.038***	0.012***
	[38.23]	[8.91]	[7.39]	[4.91]
R^2	0.00	0.01	0.01	0.45
Weeks	936	928	928	928
Firms	5,609	4,912	4,912	4,908
Obs.	1,976,163	1,736,945	1,736,945	1,733,939

This table reports panel regressions with clustered standard errors by firm and week (Petersen (2009)) with the slope of implied volatility as the dependent variable. The sample period is January 1996 to December 2013. T-statistics are reported in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

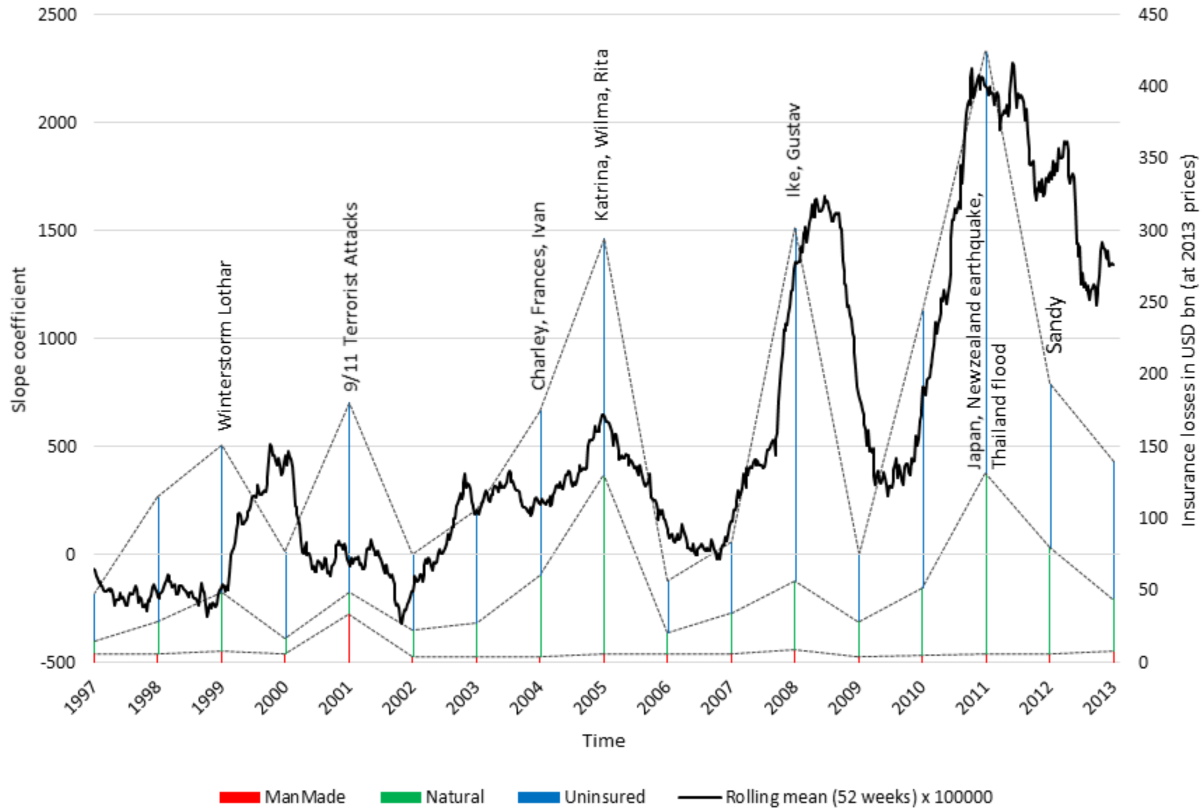
6.4 Linking catastrophe risk with the slope of implied volatility

As a result of an active primary market for catastrophe risk and ex-post figures for insured (and uninsured) losses caused by catastrophic events, we can further investigate how the implied volatility slope of P&C insurers is related to the catastrophe market after controlling for all firm-specific parameters. For that purpose, we extract the slope coefficient on $INSURANCE_{i,t}$ from cross-sectional Fama-MacBeth (1973) regressions. Because insurance losses are only available on a yearly basis, we calculate in a first run the 12-month rolling mean of the extracted slope coefficient on $INSURANCE_{i,t}$.

When we illustrate the data on total losses, available from Swiss Re, against the rolling coefficient we observe a matching effect between the two time series (Figure 4). Several observations must be highlighted. First, the graph not only shows insured but also uninsured losses, which might suggest that market participants anticipate the full losses correctly but cannot predict how much of the losses are indeed insured.[24] Second, the data shows worldwide losses. Given the strong interconnectedness between insurers - especially reinsurers - around the globe, it is not far-fetched to assume that market participants react to catastrophic news from the entire world, such as the Tohoku earthquake in Japan in 2011 (which caused the Fukushima incident). The third point we want to highlight is that the slope coefficient does not react to man-made disasters, specifically the 9/11 Terrorist Attacks. Because such an event has an impact on the entire economy, P&C insurers do not react in isolation despite an increase in the implied volatility slope during that time. The last point to address is the discrepancy between the coefficient and the insurance losses in the year 2000. One explanation is that winterstorm Lothar occurred between December 25 and December 27, 1999, and thus total losses were assigned to that year. If these losses were more appropriately assigned to year 2000, both figures would align much better.

[24] Anecdotal evidence supports this idea. During Hurricane Sandy, cat bonds issued by Chubb Corporation were oversold under the impression that these cat bonds would be triggered given the strong underwriting of Chubb in flood insurance. However, these predictions were not met, and prices heavily recovered (`http://www.artemis.bm/blog/2012/11/12/catastrophe-bond-prices-recover-some-sandy-losses-last-week/`).

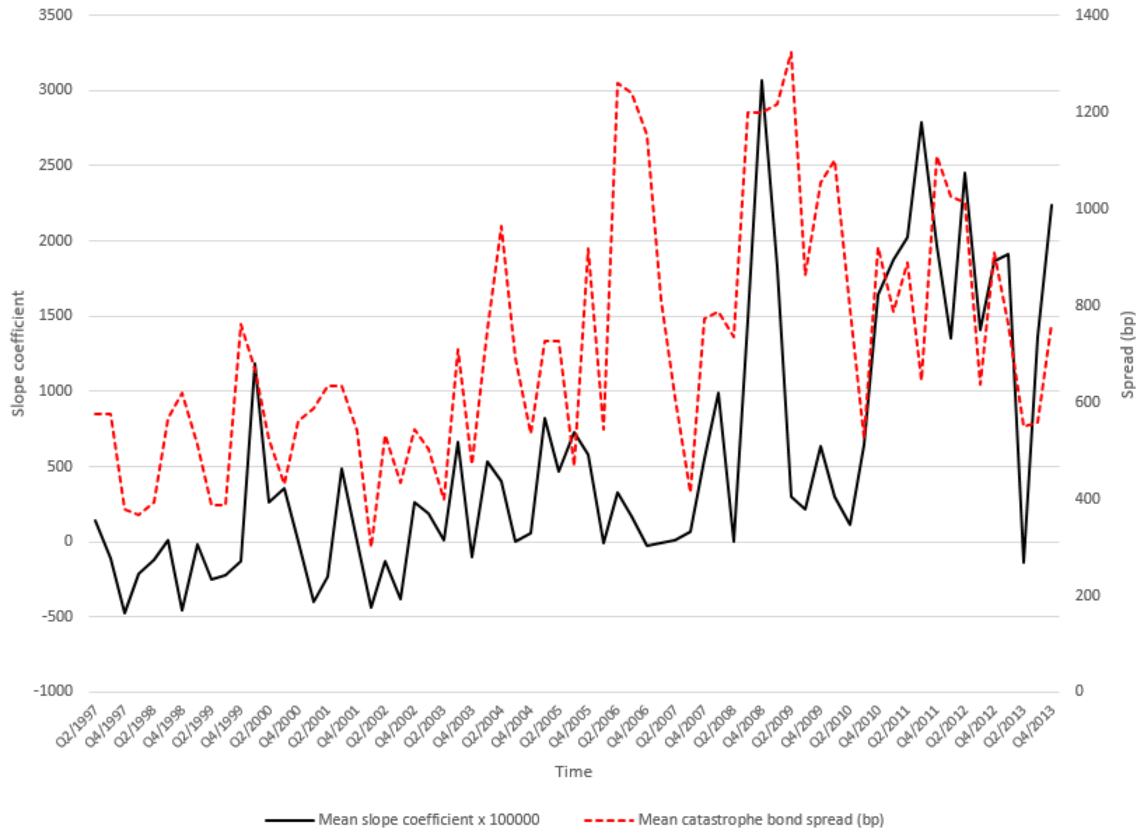
Figure 4: Total losses and the slope coefficient



This figure illustrates the 12-month rolling mean of the slope coefficient on $INSURANCE_{i,t}$ (black solid line) extracted from weekly cross-sectional regressions (i.e., Fama-MacBeth (1973) regression) with all control variables described under Formula (24). At the end of each year, global total losses from man-made (red bar), natural (green bar), and uninsured (blue bar) catastrophes are indicated. The graph also highlights the most severe catastrophes during that year. Data on insured and uninsured losses are retrieved from the *sigma* world insurance database provided by Swiss Re Economic Research & Consulting.

Despite this first indication of the implied volatility smile being connected to catastrophe risk, hard evidence is still missing. We thus turn to the catastrophe bond market. Data for catastrophe bond spreads is available on a quarterly basis. This time we start by showing the quarterly means of the slope coefficient on $INSURANCE_{i,t}$ against the quarterly mean spread of catastrophe bonds at issuance. Figure 5 illustrates the time series.

Figure 5: Catastrophe bond spreads and the slope coefficient



This figure illustrates the quarterly means of the slope coefficient on $INSURANCE_{i,t}$ (black solid line) against the quarterly mean spread of catastrophe bonds at issuance over the risk free rate (red dotted line). The spread is expressed in basis points. To compare both time-series, the slope coefficient is multiplied by 100,000.

We find a 49.4% correlation between catastrophe bond spreads and our mean coefficient. Despite this high correlation, it is not a perfect correlation. Two main possible reasons for this come to mind. First, our implied volatility measure does not contain pricing components which, in contrast, can be observed in the cat bond market. This is particularly pronounced in the graph for the period after Hurricane Katrina in which the implied volatility smile reacts to Katrina itself, but only marginally to increasing prices during the 2006 period with record-high prices. A second reason could be that the securitization of catastrophe risk is not representative for the entire U.S. P&C insurance industry. To address the first point, we run time-series regressions in a multivariate setting. We start with an univariate regression in which the quarterly mean spread of catastrophe bonds at issuance, CAT_t, is the dependent variable.

Braun (2016) identified the pricing components of cat bonds in the primary market (i.e., the yields at issuance) and thus we can decompose CAT_t in its individual risk drivers. Three parameters are important for our aggregate catastrophe risk measure. First, the expected loss, EL_t, which refers to the losses predicted by models for a specific tranche of cat bonds and, second, the default spread from bond markets. Specifically, we use the Bank of America Merrill Lynch U.S. High Yield BB Option-Adjusted Spread, $BBSPR_t$, which is defined as the yield index for the BB-rated bonds over the Treasury rate.

Table 9: Implied volatility slope and ILS

	(I)	(II)	(III)
CAT_t	1.636***	1.476***	
	[3.18]	[3.01]	
EL_t			3.131***
			[3.17]
$BBSPR_t$			1.514***
			[2.92]
$ROLX_t$			3.287
			[0.54]
$orthCAT_t$			0.521
			[0.77]
$SLOPE500_t$		7.943	
		[1.61]	
Intercept	-619.091**	-1,033.053***	-820.772
	[-2.05]	[-3.29]	[-1.47]
Adj. R^2	0.23	0.29	0.29
Obs.	67	67	67

This table reports time series regressions of quarterly means of the slope coefficient on $INSURANCE_{i,t}$ as dependent variable and ILS related variables as explanatory variables. As an additional control, the slope of the S&P500 is also included ($SLOPE500_t$). CAT_t is the quarterly mean yield spread of catastrophe bonds at issuance over the risk free rate. EL_t is the average expected loss of all catastrophe bond tranches. $BBSPR_t$ is the yield of the BofA Merrill Lynch US High Yield BB Option-Adjusted Spread. $ROLX_t$ is the Lane Financial LLC Synthetic Rate on Line Index. $orthCAT_t$ is the orthogonalized catastrophe bond yield spread on EL_t, $BBSPR_t$, and $ROLX_t$. T-statistics are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 3. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The third parameter is the rate-on-line index, $ROLX_t$, which addresses the price dynamics of reinsurance contracts. This price dynamic is known as the reinsurance cycle and a well-known phenomenon for increasing reinsurance prices after catastrophes to make up for the incurred losses. This pricing component is in fact not directly related to immediate tail risk and thus should be the least relevant pricing component with respect to the implied volatility smile. Table 9 presents the results.

Column (I) corroborates the high correlation result and what we have already seen in Figure 5 - that the spread of catastrophe bonds at issuance, CAT_t, is significantly related to the slope coefficient on $INSURANCE_{i,t}$ and thus the implied volatility smile. Column (II) runs a control regression with the implied volatility slope of the S&P500 as independent variable, $SLOPE500_t$, to ensure that the results are not driven by other market factors. Column (III) then decomposes CAT_t in its individual risk factors, EL_t, $BBSPR_t$, and $ROLX_t$. All remaining pricing components are included in the orthogonalized cat bond spread, $orthCAT_t$, on the three risk factors. As expected, EL_t is the most important driver of the implied volatility smile of P&C insurers, showing clear evidence that the implied volatility slope is indeed related to natural catastrophe risk. Furthermore, we see that price dynamics, i.e., the reinsurance cycle, $ROLX_t$, have no impact on the implied volatility smile. This is what we expected, given a missing urgency of potential default due to price dynamics. The most challenging result, though, is the highly significant BB Option-Adjusted Spread, $BBSPR_t$. Up to this point, we assumed that our difference-in-difference approach (i.e., P&C insurers vs. non-financials) would extract the financial distress component if both groups react identically to economic stress. The fact that the spread is significant, though, shows that the implied volatility of P&C insurers has a remaining reaction towards economic shocks and that our approach did not fully disentangle catastrophe risk from economic distress. Overall, our results show that the implied volatility slope is indeed related to catastrophe risk.

6.5 Event study

Having analyzed catastrophe risk in a multivariate framework, we now conduct an event study to control for the reaction of the implied volatility slope around 12 natural catastrophes in the United States between January 1996 and December 2013.[25] For that purpose, we identify the costliest natural catastrophes related to hurricanes and storms in the United States during that period.[26] Specifically, we investigate 11 hurricanes and one tropical storm listed in Appendix C, sorted by first appearance and differentiated by peril, first appearance, landfall, end date, geographic region, type of event, insured loss as documented,

[25] We choose these 12 events based on Swiss Re's 2014 Sigma Report which identifies 40 of the costliest catastrophic events between 1970 and 2013 (`http://media.swissre.com/documents/sigma1_2014_en.pdf`). Over our sample period 12 natural catastrophes occurred in the U.S. (excluding Hurricane Ike).

[26] Note that the analysis based on the largest catastrophes in the U.S. ex-post needs to be interpreted cautiously, because a look-ahead bias is introduced by considering catastrophes of which the final costs to insurance companies is known sometime after the event.

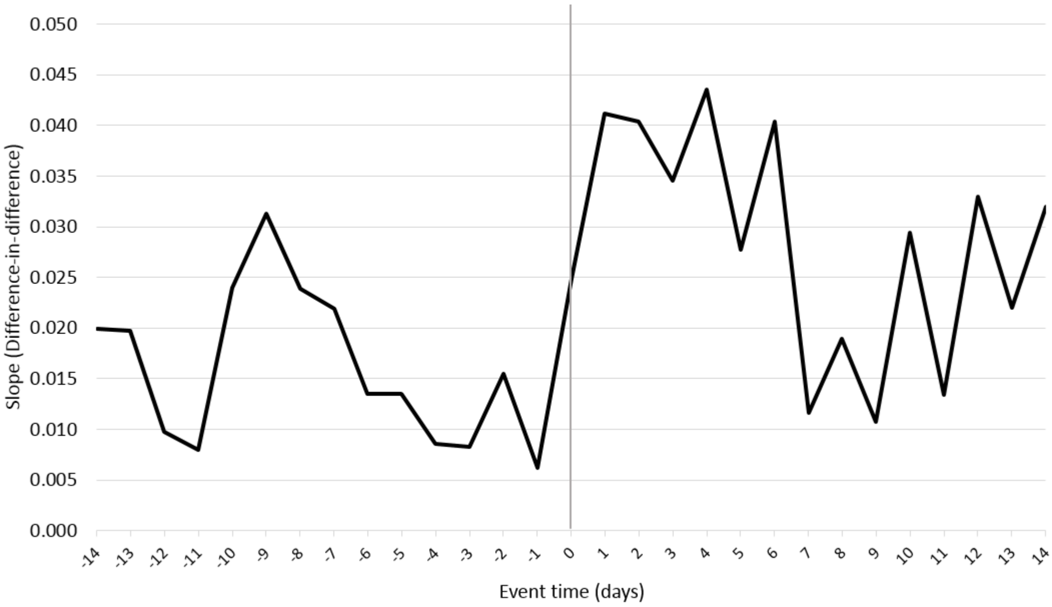
and the ranking of the loss.[27]

The question is whether the steeper slope of insurers is simply higher (due to other unknown factors) or whether the slope shows some reaction around the peak event of a catastrophe. If investors anticipate catastrophes or expect losses to insurance companies after the peak of the event to be extremely high, the implied volatility slope might be significantly larger for P&C insurers than options on non-financials.

Although it can take several months or even years until claims by policyholders are settled, first rough estimates of the damages are reported within the first two weeks after the event. We calculate the daily difference in slopes between P&C insurers and non-financials (difference-in-differences) around a natural catastrophic event. The time frame is 14 business days before and 14 days after landfall, where landfall is defined as day zero. In case of multiple landfalls, the first landfall is assigned as day zero. If landfall occurs on a weekend or a holiday, we use the following trading day as the day of landfall. Results on the difference-in-differences between the implied volatility smile of P&C insurers and non-financials are visualized for each day in Figure 6. We see that the slope difference is constantly above zero during the event period, but we also see that the slope difference peaks the first time nine business days before landfall. This is somewhat surprising, as it is well in advance before the average first appearance in our sample (ca. 5 days; see Appendix C). An explanation could be the hurricane seasons of 2004 and 2005, during which 7 out of 12 hurricanes occurred in close sequence. Thus, effects from the previous hurricane are possibly confounding the period before the next hurricane.

[27]There were no earthquakes in the U.S. during our sample period, and we exclude Hurricane Ike from our event study, because it occurred at around the same time as the peak of the financial crisis and the collapse of Lehman brothers. We include the only tropical storm Allison because of the large insured losses it incurred. We also exclude the 9/11 terrorist attacks as they not only financially affected insurers but also the entire economy.

Figure 6: Event study



This figure shows the difference in slopes between P&C insurers and non-financials (difference-in-difference) around a natural catastrophic event. The time frame is 14 business days before and 14 days after landfall. Landfall occurs on day zero. In case of multiple landfalls, the first landfall is used as day zero. If multiple events occur during a short period of time and the slope difference would be categorized both as pre- and post event, we only account for it once in the pre-event period but not again in the post-event period.

We then ask the question whether the post-event slope is higher than the pre-event slope. As we already accounted for the slope of the control group, we conduct a parametric t-test and non-parametric Wilcoxon rank-sum test between the two slopes. Table 11 reports the test results and the slope difference before and after the event. Both the parametric and non-parametric test show a significantly steeper slope after the event, again, emphasizing the fact that the slope reacts to natural catastrophes.[28]

[28]Note that the average pre- and post-slopes in the graph do not fully align with the numbers in Table 11, because there are events with more observations (i.e., options) than others and consequently have more weight, whereas the graph averages all observations on a specific day.

Table 10: Pre- and post-event comparison of the difference-in-difference slope

	Pre-Slope	Post-Slope	*Unpaired two-sided t-test*	*Wilcoxon test*
$SLOPE_{i,t}$	0.017	0.032	0.015***	0.003***
			[3.76]	[3.00]
Obs.	4097	3422		

This table compares the time period in the difference in slopes between P&C insurers and non-financials (difference-in-differences) 14 days before and 14 days after a hurricane landfall. All hurricanes in the United States between 1996 and 2013 are considered (Hurricane Ike is excluded, as it occurs around the same time as the Lehman collapse). An unpaired two-sided t-test is used to test the means before and after the event period. The median difference is reported and the non-parametric Wilcoxon–Mann–Whitney rank-sum test is applied. T-statistics and z-statistics are reported in brackets, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

7 Robustness tests

This section runs several robustness tests with respect to the sample and time period. The first robustness test refers to other financial institutions as a control group. The second test addresses the seasonality of catastrophes (i.e. hurricane season vs. non-hurricane season) whether the effect is constant over time and whether the financial crisis had an impact on the slope effect.

7.1 Other financial institutions and systemic relevance

In the previous sections we focused on options written on stocks from the non-financial sector as a control group. We argued that options written on stocks from the financial sector might create some confounding effects, such as systemic risk exposure, which become prevalent in extreme scenarios, or government guarantees or a diffusion of catastrophe risk through stakes in P&C insurers (e.g., bancassurance).

In this section, we want to address this issue by including other financial companies and comparing them with P&C insurers. For that purpose we select all put options in OptionMetrics with SIC codes between 6000 and 6999, except, of course P&C insurers (SIC code 6331), which comprise our experimental group. We run the same regressions as before. Note that our sample size is strongly reduced when running regressions with $LEVERAGE_{i,t}$ and $SIZE_{i,t}$ due to the lower availability of accounting information for financial institutions in COMPUSTAT. We thus run our regressions both with and without these two variables. Results for the variable of interest $INSURANCE_{i,t}$, however, remain robust in all specifications. Furthermore, we include a dummy variable being one for all systemically important financial institutions (SIFI) except for AIG.[29] AIG is the only company which is both a SIFI and a P&C insurer. It might be that our results are driven by AIG and that the slope of AIG is steeper than for the rest of the P&C insurers. We thus look at AIG separately and include a dummy variable, $AIG_{i,t}$, being one if the company is AIG and zero otherwise. The $SIFI_{i,t}$ dummy variable ought to capture any effect in their implied volatility smile. On the one hand, government guarantees could reduce the steepness of the slope, which is what Kelly, Lustig, and Nieuwerburgh (2015) observe in index options. Since we are looking at individual options of financial institutions, this effect might also exist in a reduced form, but it could also be that the connectivity of the financial sector and associated spillover effects translate in steeper slopes of the implied volatility. Results are reported in Table 11.

[29] A complete list of SIFIs can be found in Appendix D. Information on systemically important banks and insurers is retrieved from the Financial Stability Board (`www.fsb.org/wp-content/uploads/r_141106b.pdf` and `www.fsb.org/wp-content/uploads/FSB-communication-G-SIIs-Final-version.pdf`). Our selection of SIFIs refers to those identified by November 2014.

Table 11: Financial institutions

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
$INSURANCE_t$	0.010***	0.006***	0.002***	0.004***	0.014***	0.013***	0.012***	0.004***	0.006***
	[4.70]	[3.74]	[3.50]	[4.54]	[3.11]	[3.03]	[2.71]	[2.62]	[4.03]
$SIFI_t$	0.006*	-0.003*	-0.001*	-0.002**	0.005	-0.007	-0.006	-0.002	-0.003***
	[1.85]	[-1.81]	[-1.76]	[-2.44]	[1.17]	[-1.28]	[-1.13]	[-1.21]	[-2.70]
AIG_t	-0.030***	-0.030***	-0.011***	-0.015***	-0.040***	-0.042***	-0.039***	-0.013***	-0.016***
	[-3.60]	[-4.73]	[-4.33]	[-5.25]	[-9.00]	[-7.75]	[-7.34]	[-7.08]	[-11.33]
$IVATM_t$		-0.038***	-0.016***	-0.013***		0.038***	0.016	0.006	-0.005
		[-3.62]	[-3.73]	[-4.53]		[3.36]	[1.18]	[1.01]	[-1.32]
$LEVERAGE_t$		0.004***	0.001***			0.003**	0.003**	0.001**	
		[4.05]	[3.71]			[2.21]	[2.46]	[2.14]	
$SIZE_t$		-0.003***	-0.001***			-0.001	-0.002*	-0.000	
		[-2.88]	[-2.95]			[-1.01]	[-1.72]	[-1.15]	
$BETA_t$		0.009***	0.003***	0.008***		0.007**	0.010***	0.003**	0.012***
		[4.59]	[4.27]	[12.13]		[2.47]	[3.02]	[2.37]	[13.48]
$VOLUME_t$		0.000**	0.000	0.000		0.000	0.000	0.000	-0.000*
		[2.29]	[1.14]	[1.36]		[0.16]	[0.18]	[0.07]	[-1.90]
$CALLPUTOI_t$		-0.000	-0.000	0.000		-0.010***	-0.009***	-0.003***	-0.001
		[-0.04]	[-0.56]	[0.50]		[-3.11]	[-3.06]	[-2.88]	[-1.53]
$SLOPE500_t$							0.048	0.055	0.030
							[0.72]	[1.48]	[1.01]
$IVATM500_t$							0.094**	0.016	0.033**
							[2.55]	[0.91]	[2.55]
$SLOPE_{t-1}$			0.684***	0.708***				0.677***	0.695***
			[91.38]	[115.76]				[78.86]	[90.81]
Intercept	0.039***	0.072***	0.024***	0.008***	0.045***	0.036***	0.027**	0.008*	-0.005***
	[16.54]	[6.83]	[6.56]	[8.15]	[26.92]	[3.17]	[2.35]	[1.71]	[-2.94]
Avg. R^2	0.01	0.10	0.52	0.54					
R^2					0.00	0.01	0.01	0.47	0.52
Weeks (cluster)	936	928	928	935	936	928	928	928	935
Firms (cluster)					1699	874	874	873	1566
Obs.	477,025	290,056	289,089	435,522	477,025	290,056	290,056	289,089	435,522
Regression type	*FMB*	*FMB*	*FMB*	*FMB*	*Pooled*	*Pooled*	*Pooled*	*Pooled*	*Pooled*

This table reports Fama-MacBeth (1973) regressions and pooled regressions with clustered standard errors by firm and week (Petersen (2009)) with the slope of implied volatility as dependent variable. The control group ($INSURANCE_t = 0$) consists of all financial institutions with SIC codes between 6000 and 6999 (excluding P&C insurers with SIC code 6331). $SIFI_t$ is a dummy variable taking the value of one if the financial institutions is considered systemically relevant (excluding AIG) and zero otherwise. AIG is a dummy variable taking the value one for American International Group and zero otherwise. All other controls are as previously defined. The sample period is January 1996 to December 2013. T-statistics for Fama-MacBeth regressions are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

We see that the economic size of the coefficient on $INSURANCE_{i,t}$ has decreased by approximately half compared to the previous regressions with non-financials as the control group, suggesting that some of our concerns regarding other financial institutions might be true. To our surprise though, AIG is not a driving force of our results at all. Quite the contrary, $AIG_{i,t}$ shows a highly significant negative coefficient, meaning that AIG's implied volalitity smile is much flatter than the implied volatility smile of other P&C insurers. SIFIs, in general, also do not confound our results. Although not being statistically significant under all specifications the overall direction of the $SIFI_{i,t}$ dummy variable is negative, meaning a flatter slope as well. Overall, results are robust against this additional control group.

7.2 Reinsurers, insurance losses, and tail risk mitigation

One of the typical features of insurers is assuming risk, not only from policyholders but also from other insurers which is termed reinsurance.[30] The question is then, whether insurers ceding more of their (tail) risk to reinsurers have a less steep implied volatility slope than those which purchase less reinsurance. In addition, those considered as reinsurers might have a steeper implied volatility slope because they sell reinsurance. Technically, excess-of-loss reinsurance, a non-proportional reinsurance type, is the reinsurance type we are interested in, as it caps the losses in the tail of the loss distribution. However, the datasource (ORBIS) we use to determine the reinsurance coverage does not differentiate between the two reinsurance types which is a limitation of this investigation.

The following sample only consists of reinsurers and primary insurers but does not employ a control group as in the previous sections (i.e., non-financials).[31] The dummy variable $REINSURER_{i,t}$ takes on the value of one if the insurer at hand is a reinsurer and zero if it is a primary insurer. Following Cummins and Phillips (2005), our definition of a reinsurer is based on the North American Industry Classification System (NAICS) code 524130 for property/casualty reinsurance. Because of tax reasons, and higher investment flexibility, most of the reinsurers in our sample are headquartered on the Bermudas. Our sample consists of 10 Bermuda-based, 2 U.S.-based, 1 Swiss-based, 1 Luxembourg-based, and 1 Cayman Islands-based reinsurers (P&C insurers marked by (R) in Appendix B). These 15 reinsurers are a subsample of the 67 P&C insurers.

To further investigate tail risk mitigation techniques, we retrieve data on reinsurance coverage for each insurer at each year from the ORBIS database. Reinsurance coverage ($REINSCOVER_{i,t}$) is defined as $(1 - \frac{net\ premiums}{premiums\ written})$. The difference between gross premiums and net premiums is the absolute amount of reinsurance which an insurer purchases. We then run the same regressions described in Section 4 with the implied volatility slope on the left-hand side, but in a reduced sample of primary insurers and reinsurers. In addition, we include an interaction term between being a reinsurer and the value of reinsurance coverage. As before, we control for all other firm- and market-specific variables. We run both Fama-MacBeth (1973) regressions and panel regressions with clustered standard errors by firm and week

[30] There are two main categories of reinsurance: proportional and non-proportional. Proportional means that both the primary insurer and the reinsurer share a predefined ratio of the incurred losses. In contrast, non-proportional requires the primary insurer to cover all losses up to a predefined threshold. When that threshold is exceeded, the reinsurer jumps in and covers the following losses up to a maximum.

[31] Because non-financials do not purchase reinsurance coverage and we do not know whether, how much, and what type of primary insurance policies they buy.

(Petersen (2009)). Table 12 presents the results.

Table 12: Reinsurers and reinsurance cover

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
$REINSURER_{i,t}$	-0.005*	-0.009***	-0.004***	0.002	-0.006	-0.006	-0.002
	[-1.70]	[-2.58]	[-2.72]	[0.14]	[-0.47]	[-0.47]	[-0.50]
$REINSCOVER_{i,t}$	0.038***	0.022**	0.011**	0.031	-0.013	-0.009	-0.004
	[3.66]	[2.12]	[2.04]	[1.10]	[-0.45]	[-0.34]	[-0.38]
$REINSURER_{i,t} \times REINSCOVER_{i,t}$	0.012	0.040**	0.014	0.067	0.133	0.125	0.042
	[0.73]	[2.13]	[1.63]	[0.73]	[1.52]	[1.40]	[1.35]
$IVATM_{i,t}$		0.049**	0.022*		0.093***	0.076*	0.036*
		[2.13]	[1.68]		[2.88]	[1.68]	[1.82]
$LEVERAGE_{i,t}$		0.003	0.003*		0.002	0.003	0.000
		[1.60]	[1.93]		[0.34]	[0.41]	[0.15]
$SIZE_{i,t}$		-0.004**	-0.002*		-0.009***	-0.009***	-0.002**
		[-2.24]	[-1.82]		[-3.29]	[-3.32]	[-2.46]
$BETA_{i,t}$		0.001	-0.001		0.017*	0.017*	0.005
		[0.26]	[-0.18]		[1.84]	[1.93]	[1.44]
$VOLUME_{i,t}$		0.000	0.000		-0.000	-0.000	-0.000**
		[0.69]	[0.42]		[-1.03]	[-0.77]	[-2.21]
$CALLPUTOI_{i,t}$		-0.000	-0.001		-0.011	-0.010	-0.004*
		[-0.11]	[-0.56]		[-1.63]	[-1.48]	[-1.74]
$SLOPE500_{i,t}$						0.169	0.099*
						[1.27]	[1.80]
$IVATM500_{i,t}$						0.013	-0.018
						[0.15]	[-0.49]
$SLOPE_{i,t-1}$			0.632***				0.654***
			[40.79]				[30.16]
Intercept	0.044***	0.060***	0.025***	0.051***	0.093***	0.083***	0.024**
	[12.11]	[3.62]	[3.04]	[9.34]	[2.97]	[2.94]	[2.45]
Avg. R^2	0.11	0.44	0.68				
R^2				0.01	0.05	0.05	0.45
Weeks (cluster)	935	923	923	935	923	923	923
Firms (cluster)				65	65	65	65
Obs.	27,511	27,085	27,063	27,511	27,085	27,085	27,063
Regression type	*FMB*	*FMB*	*FMB*	*Pooled*	*Pooled*	*Pooled*	*Pooled*

This table reports Fama-MacBeth (1973) regressions and pooled regressions with clustered standard errors by firm and week. The dependent variable is the slope of implied volatility. The sample period is January 1996 to December 2013. T-statistics for Fama-MacBeth regressions are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Results regarding the reinsurer and primary insurer sample are not as distinct as the ones we observe for P&C insurers against non-financials and other financial institutions in previous sections. The Fama-MacBeth (1973) regressions in Column (I), (II), and (III) show that the implied volatility slope is less steep for reinsurers compared to primary insurers and that reinsurance coverage increases the steepness of the slope. Both results appear counterintuitive at first unless investors believe that buying reinsurance is a signal for being more at risk and thus in need for more protection. In contrast, a reinsurer only bears losses up to a certain limit which could be an explanation why investors believe catastrophe risk is limited, too.

Although these results are statistically significant based on Fama-MacBeth (1973) regressions, they cannot be confirmed using pooled regressions with clustered standard errors by firm and week. As Petersen (2009) shows, standard errors under Fama-MacBeth (1973) regressions are biased downwards if there is a firm effect present. Because we are now analyzing the same industry (i.e., P&C insurers) the presence of a common firm effect is comprehensible. Overall, this suggests that investors do not or are not able to distinguish between the risk profile of reinsurers and primary insurers and the respective reinsurance coverage they purchase.

7.3 Seasonality, subperiods, and the financial crisis

In the event study, we have seen that the implied volatility slope is affected by hurricanes and significantly larger after the event with an additional reaction approximately ten days before the event. This might suggest that the implied volatility slope is steeper during the hurricane season and lower during the non-hurricane season. However, assuming that insurers are constantly exposed to catastrophes which are difficult to predict and not even seasonal, e.g., an earthquake, a man-made disaster, or an off-season hurricane / natural event, then the slope should be larger throughout the year. According to the National Hurricane Center, the U.S. hurricane season in the Atlantic starts June 1st and ends November 30th, whereas the Eastern Pacific hurricane season already starts May 15th but also ends November 30th. To control for potential seasonal effects in implied volatilities of P&C insurers due to hurricanes, we create a dummy variable, $HURSEASON_{i,t}$, being one during the overlapping Eastern Pacific and Atlantic hurricance months of May to November and zero during the months of December to April. The interaction term between $INSURANCE_{i,t}$ and $HURSEASON_{i,t}$ should then be significant and positive if there is indeed a seasonal effect in P&C options. Table 13 reports the multivariate results.[32]

[32]We only report pooled regressions because $HURSEASON_{i,t}$ is a time dummy.

Table 13: Seasonality

	(I)	(II)	(III)	(IV)
$INSURANCE_{i,t}$	0.024***	0.022***	0.023***	0.007***
	[4.93]	[4.48]	[4.55]	[4.17]
$HURSEASON_{i,t}$	-0.001	-0.001	-0.002	-0.001
	[-0.34]	[-0.51]	[-1.12]	[-0.99]
$INSURANCE_{i,t} \times HURSEASON_{i,t}$	0.001	0.001	0.001	0.001
	[0.50]	[0.44]	[0.43]	[0.95]
Controls	NO	YES	YES	YES
R^2	0.00	0.01	0.01	0.45
Weeks	936	928	928	928
Firms	5,609	4,912	4,912	4,908
Obs.	1,976,163	1,736,945	1,736,945	1,733,939

This table reports panel regressions with clustered standard errors by firm and week (Petersen (2009)). $HURSEASON_{i,t}$ is a dummy variable taking the value of one for the Atlantic hurricane season June to November and zero for the months December to May. $INSURANCE_{i,t} \times HURSEASON_{i,t}$ is an interaction term between the dummy variable $INSURANCE_{i,t}$ and $HURSEASON_{i,t}$. The sample period is January 1996 to December 2013. T-statistics are reported in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Column (I) does not include any control variables. The interaction term $INSURANCE_{i,t} \times HURSEASON_{i,t}$ shows no significance. When controlling for the same variables as in Section 6.3, this result remains robust. Overall we do not find a seasonal effect in implied volatilities. That is, the implied volatility is not steeper during the hurricance season, which suggests that derivatives on P&C insurers are constantly more expensive than their non-financials counterparts throughout the year.

Having addressed the seasonal aspect within the years, we now address changes in the implied volatility over the sample period. With Hurricane Katrina being the costliest and most devastating hurricane in U.S. history, we separate our sample in two equally long subperiods of nine years, where 1996 until 2004 is the pre-Katrina subperiod and 2005 until 2013 is the post-Katrina subperiod. Possibly the attitude towards natural catastrophes changed after that among investors, speculators, and market makers. We run Fama-MacBeth (1973) regressions and pooled regressions as in the previous sections on the two subsamples. Results are shown in Table 14 and show that the slope of P&C insurers indeed changed compared to non-financials in the post-Katrina period. Specifically in univariate pooled and Fama-MacBeth (1973) regressions, the slope is both statistically and economically much smaller compared to the post-Katrina period. When we control for the firm and market-specific variables we even observe an insignificant effect on the variable of interest, $INSURANCE_{i,t}$. One explanation could be that, similar to the market crash of 1987 introducing the implied volatility smile, Hurricane Katrina could have had a similar effect in creating an additional risk awareness (or "additional" smile) on top of the implied volatility smile. A second explanation might be the overall increase of natural disasters in the post 2005 years and thus a steeper slope.

Table 14: Subperiods

	Pre-Katrina (2005)				Post-Katrina (2005)			
	(I)	**(II)**	**(III)**	**(IV)**	**(V)**	**(VI)**	**(VII)**	**(VIII)**
$INSURANCE_t$	0.003**	0.000	0.005*	-0.000	0.030***	0.010***	0.034***	0.012***
	[2.58]	[0.51]	[1.94]	[-0.40]	[8.59]	[8.15]	[5.79]	[5.86]
$IVATM_t$		-0.046*		-0.019***		-0.016***		-0.013***
		[-1.81]		[-11.38]		[-6.32]		[-4.44]
$LEVERAGE_t$		-0.009		-0.001***		0.000		0.000
		[-1.30]		[-6.30]		[1.41]		[0.93]
$SIZE_t$		-0.003		0.000		-0.001***		-0.001***
		[-0.91]		[1.24]		[-3.68]		[-4.30]
$BETA_t$		0.001		0.005***		0.003***		0.002***
		[0.57]		[12.11]		[4.11]		[3.70]
$VOLUME_t$		0.000		0.000***		-0.000***		-0.000***
		[1.06]		[3.80]		[-5.86]		[-2.73]
$CALLPUTOI_t$		0.001		-0.004***		-0.000		0.000
		[0.73]		[-8.18]		[-0.62]		[0.19]
$SLOPE500_t$				-0.109***				0.028
				[-5.15]				[0.56]
$IVATM500_t$				0.081***				0.029
				[6.69]				[1.53]
$SLOPE_{t-1}$		0.644***		0.690***		0.654***		0.652***
		[25.19]		[103.02]		[116.23]		[94.05]
Intercept	0.027***	0.046	0.028***	0.003	0.038***	0.028***	0.038***	0.020***
	[7.05]	[1.41]	[19.11]	[1.24]	[22.01]	[8.62]	[35.98]	[5.42]
Avg. R^2	0.00	0.47			0.00	0.44		
R^2			0.00	0.50			0.00	0.43
Weeks (cluster)	468	460	468	460	468	468	468	468
Firms (cluster)			3522	2991			4434	3994
Obs.	837,594	692,521	837,594	692,521	1,138,569	1,041,418	1,138,569	1,041,418
Regression type	FMB	FMB	Pooled	Pooled	FMB	FMB	Pooled	Pooled

This table reports Fama-MacBeth (1973) regressions and pooled regressions with clustered standard errors by firm and week (Petersen (2009)), with the slope of implied volatility as dependent variable. The sample is split into two equally long time periods of nine years. The first time period is considered the pre-Katrina period (1996 - 2004), and the second period is considered the post-Katrina period (2005 - 2013). T-statistics for Fama-MacBeth regressions are reported in brackets and corrected for Newey-West (1987) autocorrelation with lags of 7. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The last potential reason we can think of is related to the financial crisis of 2008, which simply might be driving the result of a steeper slope. To control for this effect, we include a dummy variable for the financial crisis, $FinCrisis_{i,t}$, which takes on the value of one for the time between February 2008 and July 2009, which is the time frame of the financial crisis according to the National Bureau of Economic Research (NBER) based Recession Indicators for the United States and zero else. Moreover, we include an interaction term between $INSURANCE_{i,t}$ and $FinCrisis_{i,t}$ to check for a higher steepness of P&C insurers during the financial crisis. We run the regression only on the post-Katrina period (2005-2013) to ensure that our results apply to the "steep" period.[33] Results on the regressions are presented in Table 15. We find that the interaction term is insignificant in both specifications. This suggests that the steeper slope of P&C insurers is not driven by the financial crisis.

Table 15: Panel regression (Post Katrina) controlling for financial crisis

	(I)	**(II)**	**(III)**	**(IV)**
$INSURANCE_t$	0.033***	0.031***	0.012***	0.011***
	[5.77]	[4.39]	[5.87]	[4.50]
$FinCrisis_t$	0.010***	0.010***	0.003	0.003
	[3.46]	[3.40]	[1.10]	[1.07]
$INSURANCE_t \times FinCrisis_t$		0.013		0.004
		[1.22]		[0.99]
$Intercept$	0.036***	0.036***	0.020***	0.020***
	[32.4]	[32.75]	[5.44]	[5.45]
Controls	NO	NO	YES	YES
R^2	0.00	0.00	0.43	0.43
Weeks	468	468	468	468
Firms	4,434	4,434	3,994	3,994
Obs.	1,138,569	1,138,569	1,041,418	1,041,418

This table reports panel regressions with clustered standard errors by firms and week (Petersen (2009)) with the slope of implied volatility as dependent variable. The sample period covers the post-Katrina period (2005 - 2013). $FinCrisis_t$ is a dummy variable taking the one for the months between February 2008 and July 2009. $INSURANCE_t \times FinCrisis_t$ is an interaction term between the two dummy variables. T-statistics are reported in brackets. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[33] Again, because the dummy variable for the financial crisis is a time dummy we only report pooled regressions with clustered standard errors by firm and week.

8 Conclusion

This paper analyzes the implied volatility slope of P&C insurers. With P&C insurers being exposed to natural and man-made disasters and OTM put options protecting against tail risk, we argue that the exposure towards catastrophe risk should be identifiable in the implied volatility smile.

P&C insurers are particularly convenient for analyzing the relation between tail risk and option prices, because of their specific exposure to extreme events (i.e., natural disasters), their use of risk mitigation techniques against tail risk (i.e., reinsurance), and the securitization of catastrophe risk.

Our findings support this idea, both with financials and non-financials as control groups. We also confirm that the implied volatility slope of P&C insurers is related to risk premiums from the cat bond market with a correlation of 49.4%. The main drivers in the tail risk of the implied volatility slope are expected losses from natural catastrophes and the default spread (i.e., BB-rated option-adjusted yield over the treasury yield). Pricing dynamics such as the reinsurance cycle, however, do not affect the implied volatility smile. Furthermore, we find that the slope is in fact steeper on the day and after the days following a hurricane event supporting the idea that the slope reacts to potentially large losses of natural catastrophes. Lastly, we show that the effect of a steeper slope has increased over time, possibly because of an increasing number of natural disasters in recent times.

Further insights into catastrophe risk can have real effects on the pricing of catastrophe-related insurance prices. Among other things, the slope can be used as a guidance tool for the primary market how market participants evaluate the probability and compensation for catastrophe risk on average. A specific advantage of our method is the daily (high-frequency) determination of catastrophe risk using traditional option markets.

Future research might analyze how catastrophe risk deploys in other tail risk-oriented financial instruments, such as Credit Default Spreads (CDS). We established a link between put options and catastrophe bonds, but it might be of interest to emphasize how the different tail-risk-oriented instruments, i.e., put options, CDS, and catastrophe bonds interact with each other and whether arbitrage opportunities exist between them. In general, it can be asked how catastrophe risk can be financially exploited. The replication of (zero-beta) investments using put options on P&C insurers could be an efficient way for investors to earn uncorrelated returns with the market by being exposed towards catastrophe risk. The essence of this investment opportunity would be similar to a catastrophe bond but unlike catastrophe bonds which are only available to qualified investors, put options can be accessed by a wider public. The question here would be, though, whether transaction costs can be overcome. Going beyond the natural catastrophe risk aspect in option prices, it would be interesting to investigate the implied volatility smile of life insurers and their potential tail risk due to pandemics, longevity risk, or mortality risk. Lastly, future research might investigate the assumption of independence between natural catastrophes and economic downturns. Both our model and our empirical research design throughout the paper assume a clear separation between the two factors, allowing us to identify a difference-in-differences effect caused by catastrophes. However, if catastrophes exceed a critical mass, the effect between natural catastrophes and economic downturns might become indistinguishable because the natural catastrophe affects the real economy. A model which accounts for this downside correlation might thus be more appropriate.

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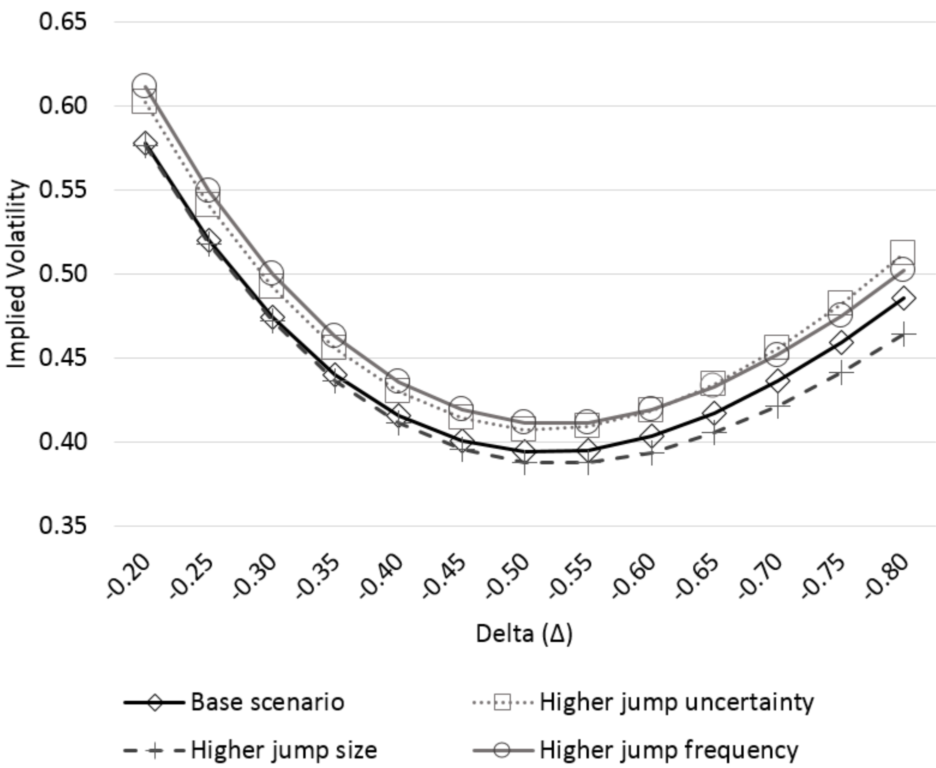
Appendix A Model sensitivity

Figure A: Modeled implied volatility smiles (P&C insurers)



This figure illustrates the modeled implied volatilities of one-month-to-expiration put options written on P&C insurance stocks for different catastrophe-related parameters. The "Base scenario" is identical to the main calibration for a P&C insurance stock in Section 3 (black line marked by downward pointing squares). The second scenario "Higher jump uncertainty" changes, ceteris paribus, the value of σ_{cat} to 0.55. The third scenario "Higher jump size" changes, ceteris paribus, the value of γ_{cat} to -0.12. The fourth scenario "Higher jump frequency" changes, ceteris paribus, the value of λ_{cat} to 1.20.

Appendix B Property/casualty insurers with options

Table B: P&C insurers

Company name	CUSIP	Company name	CUSIP
20TH CENTURY INDUSTRIES	90130N10	KEMPER CORP DE	48840110
ACE LTD **(R)**	H0023R10	LOEWS CORP	54042410
ALLEGHANY CORP DE	01717510	MAIDEN HOLDNGS LTD **(R)**	G5753U11
ALLIED WORLD ASSUR CO HLDGS AG	H0153110	MARKEL CORP	57053510
ALLSTATE CORP	02000210	MEADOWBROOK INSURANCE GROUP INC	58319P10
ALTERRA CAPITAL HOLDINGS LTD	G0229R10	MERCURY GENERAL CORP NEW	58940010
AMERICAN FINANCIAL GROUP INC NEW	02593210	MONTPELIER RES HOLDINGS LTD **(R)**	G6218510
AMERICAN INTERNATIONAL GROUP INC	02687478	MUTUAL RISK MANAGEMENT LTD	62835110
AMERISAFE INC	03071H10	NAVIGATORS GROUP INC	63890410
AMTRUST FINANCIAL SERVICES INC	03235930	ODYSSEY RE HOLDINGS CORP	67612W10
ARCH CAPITAL GROUP LTD NEW **(R)**	G0450A10	OHIO CASUALTY CORP	67724010
ASPEN INSURANCE HOLDINGS LTD **(R)**	G0538410	ONEBEACON INSURANCE GROUP LTD	G6774210
ASSURANT INC **(R)**	04621X10	PHILADELPHIA CONSOLIDATED HLG CO	71752810
AXIS CAPITAL HOLDINGS LTD **(R)**	G0692U10	PLATINUM UNDERWRITERS HLDGS LTD **(R)**	G7127P10
BERKLEY W R CORP	08442310	PROASSURANCE CORP	74267C10
BERKSHIRE HATHAWAY INC DEL	08467070	PROGRESSIVE CORP OH	74331510
C N A FINANCIAL CORP	12611710	R L I CORP	74960710
CHUBB CORP	17123210	RELIANCE GROUP HOLDINGS INC	75946410
CINCINNATI FINANCIAL CORP	17206210	RENAISSANCERE HOLDINGS LTD **(R)**	G7496G10
COMMERCE GROUP INC MASS	20064110	SAFECO CORP	78642910
EMPLOYERS HOLDINGS INC	29221810	SAFETY INSURANCE GROUP INC	78648T10
ENDURANCE SPECIALTY HOLDINGS LTD **(R)**	G3039710	SEABRIGHT HOLDINGS INC	81165610
EVEREST RE GROUP LTD **(R)**	G3223R10	SELECTIVE INSURANCE GROUP INC	81630010
FIRST MERCURY FINANCIAL CORP	32084110	STATE AUTO FINANCIAL CORP	85570710
FLAGSTONE REINSURANCE HLDGS SA **(R)**	L3466T10	TOWER GROUP INTERNATIONAL LTD	G8988C10
FRONTIER INSURANCE GROUP INC	35908110	TRANSATLANTIC HOLDINGS INC **(R)**	89352110
GLOBAL INDEMNITY PLC	G3931910	TRAVELERS COMPANIES INC	89417E10
GREENLIGHT CAPITAL RE LTD **(R)**	G4095J10	TRAVELERS PPTY CASUALTY CORP NEW	89420G10
H C C INSURANCE HOLDINGS INC	40413210	TRAVELERS PPTY CASUALTY CORP NEW	89420G40
HANOVER INSURANCE GROUP INC	41086710	UNITED FIRE GROUP INC	91034010
HARTFORD FINANCIAL SVCS GRP INC	41651510	UNIVERSAL INSURANCE HOLDINGS INC	91359V10
HILLTOP HOLDINGS INC	43274810	VALIDUS HOLDINGS LTD **(R)**	G9319H10
HORACE MANN EDUCATORS CORP NEW	44032710	ZENITH NATIONAL INSURANCE CORP	98939010
INFINITY PROPERTY & CASUALTY COR	45665Q10		

Property/casualty insurers marked by **(R)** are also reinsurers according to the North American Industry Classification System.

Appendix C Natural catastrophes in the U.S. (1996–2013)

Table C: Catastrophic events in the U.S. (1996–2013)

Peril	**First appearance (start date)**	**Landfall / Peak**	**End date**	**Geographic region of catastrophe**	**Event**	**Insured loss (indexed to 2013 in $M)**	**Rank (loss)**
Hurricane Georges	9/15/1998	9/21/1998	9/29/1998	LA, MS, AL, FL	Floods	5,240	14
Hurricane Floyd	9/7/1999	9/14/1999	9/16/1999	NC, SC, VA, MD, PA, NY, NJ, DE, RI, CT, MA, NH, VT	Heavy rain, floods	4,100	18
Tropical storm Allison	6/5/2001	6/5/2001	6/17/2001	TX, LA, MS, FL, VA, PA	Floods	4,925	15
Hurricane Charley	8/9/2004	8/13/2004	8/14/2004	FL, SC, NC	Storm surge	10,313	9
Hurricane Frances	8/25/2004	9/2/2004	9/9/2004	FL, SC, NC	Storm surge, floods	6,593	12
Hurricane Ivan	9/2/2004	9/16/2004	9/21/2004	AL, FL, GA, MS, LA, SC, NC, VA, WV, MD, TN, KY, OH, DE, NJ, PA, NY	Damage to oil rigs, storm surge, floods	17,218	5
Hurricane Jeanne	9/13/2004	9/14/2004	9/29/2004	FL, GA, SC, NC, VA, MD, DE, NJ, PA, NY	Floods, landslides	4,872	16
Hurricane Katrina	8/23/2005	8/25/2005	8/30/2005	FL, LA, MS, AL, TN, KY, IN, OH, GA.	Storm surge, levee failure, damage to oil rigs	80,373	1
Hurricane Rita	9/18/2005	9/24/2005	9/26/2005	FL, AL, MS, LA, AR, TX	Floods, damage to oil rigs	12,510	7
Hurricane Wilma	10/15/2005	10/21/2005	10/26/2005	FL	Floods	15,570	6
Hurricane Ike	9/1/2008	9/7/2008	9/15/2008	TX, LA, AR, TN, IL, IN, KY, MO, OH, MI, PA.	Floods, offshore damage	22,751	4
Hurricane Irene	8/21/2011	8/22/2011	8/30/2011	NC, VA, MD, NJ, NY, CT, RI, MA, VT	Extensive flooding	6 274	13
Hurricane Sandy	10/21/2012	10/24/2012	10/31/2012	MD, DE, NJ, NY, CT, MA, RI	Storm surge	36,890	2

Notes: Data on the events is retrieved from Swiss Re's 2014 Sigma Report. Events are presented in chronological order. Hurricane Ike is written in Italics and is not included in the event study due to the close proximity to the financial crisis. Data about appearance, landfall, and end date are from the National Hurricane Center (NHC) using the HURDAT2 dataset.

Appendix D Systemically important financial institutions (SIFI)

Table D: Systemically important financial institutions (SIFI)

	Company name	CUSIP
Banks		
	BANCO SANTANDER S A	05964H10
	BANK OF AMERICA CORP	06050510
	BANK OF NEW YORK MELLON CORP	06405810
	BARCLAYS PLC	06738E20
	CITIGROUP INC	17296742
	CREDIT SUISSE GROUP	22540110
	GOLDMAN SACHS GROUP INC	38141G10
	H S B C HOLDINGS PLC	40428040
	I N G GROEP N V	45683710
	JPMORGAN CHASE & CO	46625H10
	LLOYDS BANKING GROUP PLC	53943910
	MITSUBISHI UFJ FINANCIAL GP INC	60682210
	MIZUHO FINANCIAL GROUP INC	60687Y10
	MORGAN STANLEY DEAN WITTER & CO	61744644
	ROYAL BANK SCOTLAND GROUP PLC	78009768
	STATE STREET CORP	85747710
	SUMITOMO MITSUI FINANCIAL GP INC	86562M20
	WELLS FARGO & CO NEW	94974610
	DEUTSCHE BANK A G	D1819089
	U B S AG	H8923133
Life insurers		
	AEGON N V	00792410
	METLIFE INC	59156R10
	PRUDENTIAL FINANCIAL INC	74432010
	PRUDENTIAL PLC	74435K20
P&C insurers		
	AMERICAN INTERNATIONAL GROUP INC	02687478