Failure to Share Natural Disaster Risk

Tuomas Tomunen

Boston College Carroll School of Management

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Risk sharing and intermediary asset pricing

- Capital markets enable risk sharing in the society
- Frictions in financial intermediation can disrupt this process (He & Krishnamurthy, 2013; Brunnermeier & Sannikov, 2014)

  → Asset prices reflect intermediaries' risk exposures rather than those of end-investors
- Testing this prediction is hard due to omitted risk-factor problem (Santos & Veronesi, 2022)

This paper tests theories of risk sharing in a unique setting

1. Studies the pricing of catastrophe bonds
   - Exposed only to natural disaster risk
2. Argues that the relevant intermediary is a specialist hedge fund manager
3. Finds that 71% of security-level variation in the expected returns can be explained by the marginal utility of these intermediaries
   - Inconsistent with omitted risk factor alternatives if natural disasters are independent of marginal value of aggregate wealth (identifying assumption)

Literature

Cat bond basics

- Trigger if qualifying natural disasters occur
- Intentionally structured to minimize interest rate and credit risk
  $\rightarrow$ historical returns virtually uncorrelated with other asset classes
- Issued by (re)insurance companies and government agencies
- Account for around 20% of total reinsurance capital

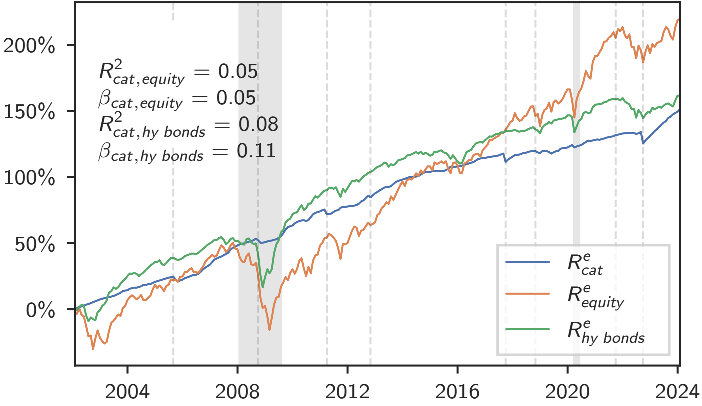
Deal Structure
Market Size
Correlations

Risk modeling

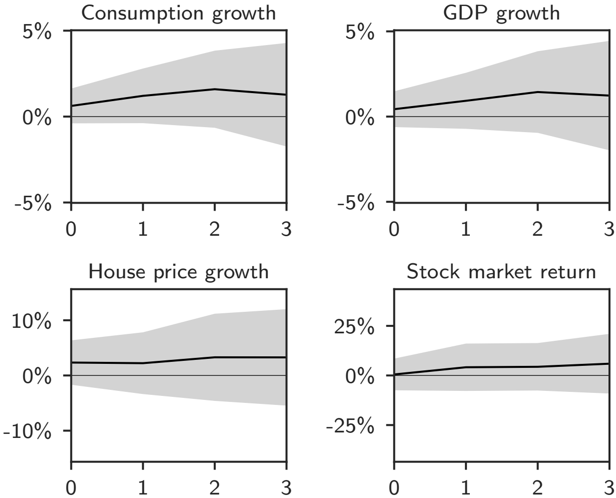
- Before issuance, sponsor hires a risk modeling company to assess actuarial risk of bond triggering
  - AIR, RMS, EQECAT
- Modelled loss summarized by three measures
  - Attachment probability
  - Expected loss (%)
  - Exhaustion probability

Risk Model
Modeling Companies

Fact 1: buying cat bonds has been extremely profitable despite low correlations with other asset classes

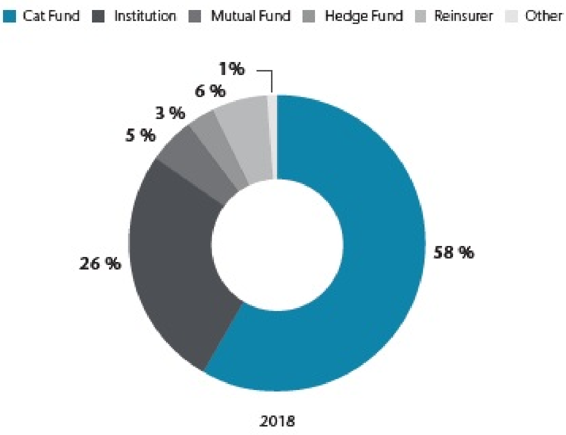


Fact 2: historical natural disasters haven't had significant macroeconomic consequences in developed countries



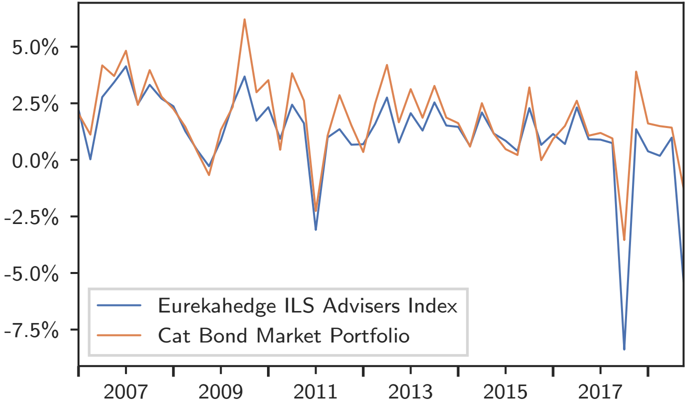
Specification

Fact 3: majority of cat bonds are held by specialist funds



Investor by Category (AON 2018)

Fact 3: majority of cat bonds are held by specialist funds



Data

Table: Summary Statistics

Panel A: Bond Characteristics (Primary Market)					
Variable	N	Mean	St Dev	Min	Max
Size ($ Million)	675	130.8	119.6	1.8	1500.0
Time to Maturity (Months)	675	36.9	13.1	5.0	120.0
Spread (%)	658	7.3	5.1	0.7	49.2
Attachment Probability (%)	657	3.2	3.2	0.0	23.2
Expected Loss (%)	661	2.3	2.3	0.0	15.8
Exhaustion Probability (%)	656	1.8	1.8	0.0	12.0
Expected excess return (%)	645	5.2	3.8	0.6	43.0
Panel B: Secondary Market					
Variable	N	Mean	St Dev	Min	Max
Turnover (%)	5,969	35.8	79.1	0.0	2000.0
Discount margin_{sheet} (%)	6,538	6.6	4.8	0.0	39.5
Discount margin_{trace} (%)	3,994	6.7	4.6	-0.3	36.9

Model

- Simple general equilibrium asset pricing model with financial intermediation similar to Gabaix, Krishnamurthy, and Vigneron (2007)
  - Outside investors can access cat bond markets only through specialized cat funds
  - Intermediation friction: fund manager must have “skin in the game” by having large amount of her own wealth tied to the fund (alternatively, pay is tied to portfolio performance)
  - Key assumption: natural disasters are independent of marginal value of aggregate wealth

Model details

Model Predictions

- Cross-section:

$$E_t(R^e_{i,t+1}) = \beta_{i,t} E_t(R^e_{cat,t+1}) \tag{1}$$

- $R^e_{cat,t+1}$ is excess return on "cat bond market portfolio"
- Time series:

$$E_t(R^e_{cat,t+1}) = \hat{\rho} \mathrm{Var}_t(R^e_{cat,t+1}) \frac{Size_t}{AUM_t} \tag{2}$$

Empirical approach

- Prediction of a simple model with intermediation frictions:

$$E_t(R^e_{i,t+1}) = \beta_{i,t} E_t(R^e_{cat,t+1})$$

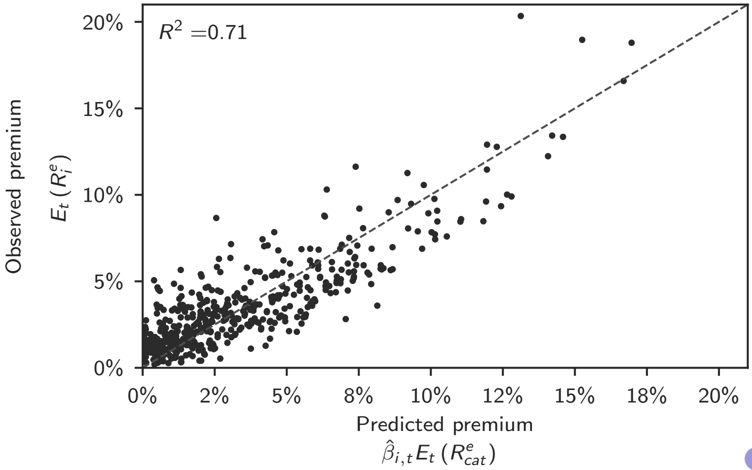
- $E_t(R^e_{i,t+1}) = s_{i,t} - el_i$
  - Key assumption: actuarial cat models' loss estimates are good proxy for investors' loss estimates

- $\beta_{i,t}$ cannot be feasibly estimated from historical data
  - Short sample, infrequent trading, highly skewed returns
  - Solution: use actuarial models to model bonds' return distributions and estimate $\beta_{i,t}$'s from simulated data

- Empirically, variation in simulated $\beta_{i,t}$ is mainly driven by:
  - Bond's expected loss
  - Relative size of bond's peril category

Details

Cross-sectional results



$\beta = 1$

$E\left(R^e_{cat}\right)$

R^2 decomposition

Cross-sectional results

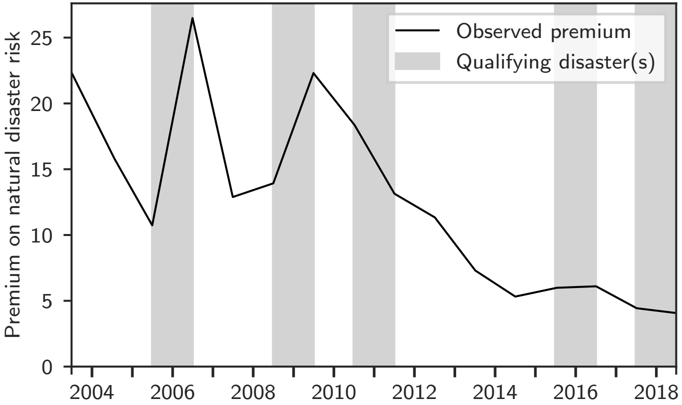
Table: Pricing of Catastrophe Market Risk

t	$\lambda_{0,t}$	(t-stat)	$\lambda_{cat,t}$	(t-stat)	$\lambda_{cat,t} - E_t\left(R^e_{cat,t+1}\right)$	(t-stat)	R^2	N	$N_{clusters}$
2003	**1.47**	16.98	**2.14**	17.42	**-1.45**	-11.78	0.73	30	12
2004	0.09	0.12	**1.54**	3.11	-0.31	-0.63	0.51	36	18
2005	**0.84**	6.56	**1.09**	12.08	**-0.88**	-9.72	0.42	34	16
2006	-2.51	-2.54	**7.62**	9.62	2.13	2.69	0.82	33	18
2007	**1.49**	3.10	**3.78**	5.01	-0.96	-1.27	0.71	40	28
2008	**1.53**	4.88	**2.86**	8.11	**-1.18**	-3.35	0.72	33	27
2009	**3.29**	5.10	**4.03**	5.14	**-2.97**	-3.79	0.71	22	17
2010	**3.10**	5.51	**1.99**	5.50	**-2.86**	-7.90	0.53	30	21
2011	1.07	1.25	2.62	2.54	-0.77	-0.75	0.42	22	15
2012	**1.21**	3.23	**4.08**	11.69	**-1.58**	-4.54	0.84	31	27
2013	**0.79**	3.75	**2.17**	8.52	**-1.02**	-4.02	0.76	42	35
2014	**1.15**	6.20	**1.39**	5.09	**-1.22**	-4.45	0.54	48	39
2015	**1.09**	7.04	**1.23**	6.85	**-1.12**	-6.22	0.60	50	39
2016	**0.90**	5.56	**1.02**	5.28	**-0.70**	-3.65	0.53	40	29
2017	0.53	2.38	**1.21**	3.64	-0.08	-0.25	0.31	46	32
2018	0.35	1.21	1.15	2.56	0.08	0.17	0.29	44	31
FM	**1.23**	9.41	**2.06**	11.67	**-1.10**	-9.02	0.49	63	

$$E_t(R^e_{i,t+1}) = \lambda_{0,t} + \lambda_{cat,t}\hat{\beta}_{i,t} + \varepsilon_{i,t+1}$$

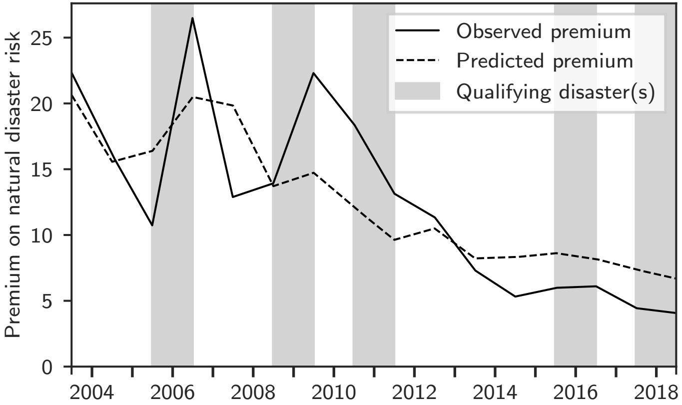
TRACE

Time series results



$$\text{Observed premium} = \frac{E_t(R^e_{cat})}{Var_t(R^e_{cat})},$$

Time series results



Observed premium $= \frac{E_t(R^e_{cat})}{Var_t(R^e_{cat})}$, Predicted premium $= \hat{\rho}\frac{Size_t}{AUM_t}$

Pooled results

- Model predicts:

$$E_t(R^e_{i,t+1}) = \beta_{i,t}\hat{\rho}\text{Var}_t(R^e_{cat,t+1})\frac{Size_t}{AUM_t}$$

- I estimate this with:

$$E_t(R^e_{i,t+1}) = \delta\beta_{i,t}F_t + \varepsilon_{i,t}$$

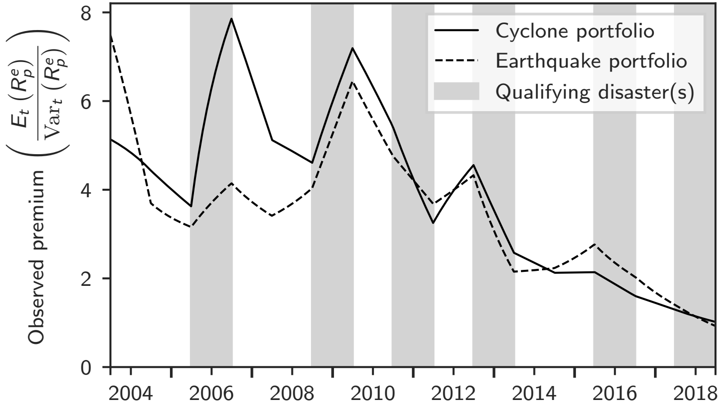
F_t	$\text{Var}_t(R^e_{cat,t+1})\frac{Size_t}{AUM_t}$	$\frac{Size_t}{AUM_t}$	$E_t(R^e_{cat,t+1})$
	5.35^{***}	0.02^{***}	0.96^{***}
	(0.38)	(0.00)	(0.05)
R^2	0.78	0.77	0.87
N	581	581	581

Alternatives

- Froot (2001)
  1. Liquidity
  2. Moral hazard & adverse selection
  3. Inefficient risk transformation
  4. Market power
- Others
  1. Peso problem
  2. Probability weighting
  3. Rare disasters
  4. Climate change risk

Liquidity
Market Power
Subsamples
Past Returns
Peso Problem
Probability Weighting

Growing climate change concerns unlikely to explain prices



Cross-section

What next?

MARKETS

State Farm Halts Home-Insurance Sales in California

State Farm is the nation's biggest car and home insurer by premium volume. It said it "made this decision due to historic increases in construction costs outpacing inflation, rapidly growing catastrophe exposure, and a challenging reinsurance market." It posted the statement on its website and referred questions to trade groups.

Source: WSJ May 26, 2023

- Ge and Tomunen (Work-in-progress): to what extent fluctuations in reinsurance premium affect home insurance costs?

Conclusion

- A model with intermediation frictions can explain premium on natural disaster risk
  - Implies a failure in risk sharing
- Potential policy tools
  1. Increase the number of available peril categories
  2. Improve access to the market
  3. Educate investors

Thank you for your attention !

Related literature

Intermediary Asset Pricing: Adrian, Etula, Muir (2014), Brunnermeier and Sannikov (2014), Chen, Joslin, Ni (2010), Etula (2013), Gabaix, Krishnamurthy, Vigneron (2007), Gârleanu, Pedersen, Poteshman (2009), Greenwood, Vissing-Jorgensen (2018), Haddad and Sraer (2018), He and Krishnamurthy (2012, 2013), He, Kelly, Manela (2017), Muir (2017), Siriwardane (2019)

Contribution: Provide evidence on intermediary pricing mechanism in a clean laboratory

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Related literature (cont'd)

Markets for Catastrophe Risk: Braun (2016), Cummins, Lalonde, Phillips (2004), Froot and O'Connell (1999, 2008), Froot (2001), Garmaise and Moskowitz (2009), Ibragimov, Jaffee, Walden (2008)

Contribution: Rule out alternative frictions proposed by Froot (2001), cross-sectional evidence with explicit pricing model

Froot (2001)

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Related literature (cont'd)

Climate Finance: Bansal et al. (2017), Barnett et al. (2019), Bolton and Kacperczyk (2019), Daniel et al. (2018), Engle et al. (2019), Hong et al. (2019), Ilhan et al. (2019), Krueger et al. (2019),

Contribution: Evidence on intermediation frictions being a major impediment for efficient allocation of natural disaster risk

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Froot (2001) assumptions and hypotheses

Assumptions:

1. Cat risk is diversifiable
   - No peso problem
2. Actuarial risk models are unbiased

Hypotheses (supply side):

1. Insufficient reinsurance capital
2. Reinsurance companies have market power
3. Corporate form for reinsurance is inefficient
4. Poor liquidity & High transaction costs
5. Moral hazard & Adverse selection

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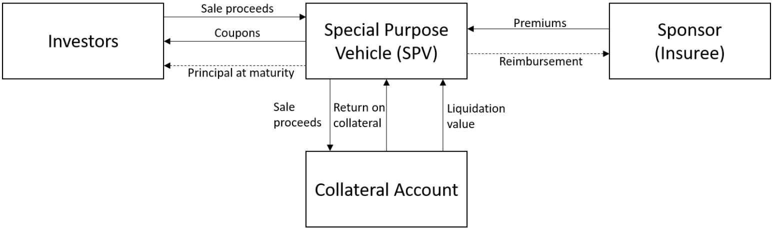
Typical deal structure



Top 10 Perils
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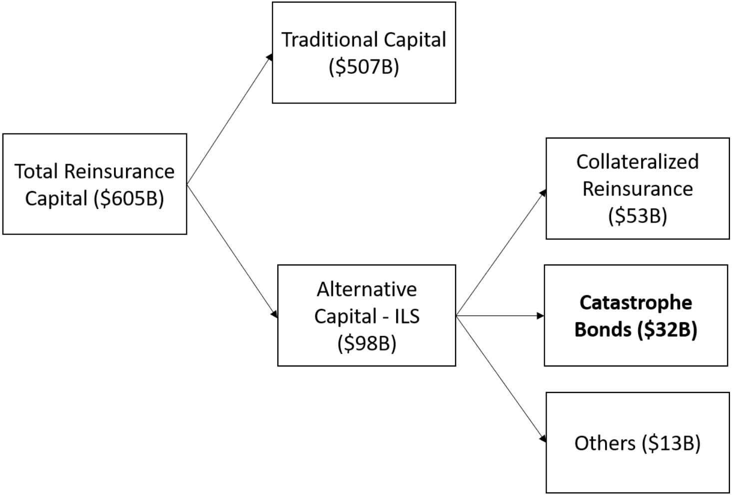
Market structure



Source: AON Benfield (2018)

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Cat bonds are uncorrelated with major asset classes

Coefficient	(1)	(2)	(3)	(4)	(5)
Intercept	0.272**	0.258*	0.266*	0.319**	0.268*
	(0.136)	(0.139)	(0.158)	(0.131)	(0.160)
Equities	0.027				0.005
	(0.021)				(0.034)
High-yield bonds		0.057*			0.038
		(0.031)			(0.051)
MBS			0.091		0.139
			(0.173)		(0.165)
Carry trade				0.031	0.008
				(0.040)	(0.049)
N	156	156	156	154	154
R^2	0.013	0.026	0.005	0.006	0.034

$$R_t^{cat} = a + b\, R_t^{other} + \epsilon_t$$

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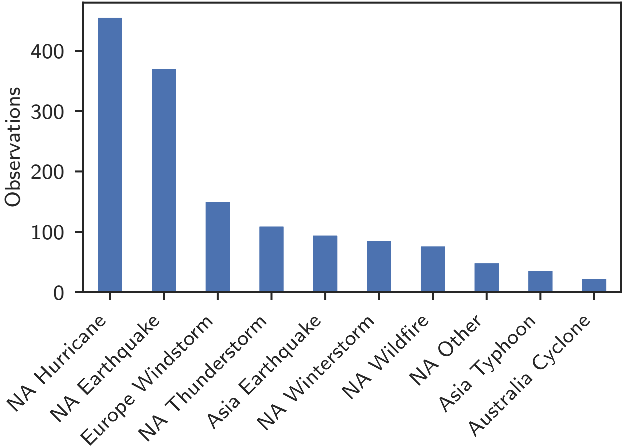
Risk modeling

- Before issuance, sponsor hires a risk modeling company to assess actuarial risk of bond triggering
  - AIR, RMS, EQECAT
- Modelled loss summarized by three measures
  - Attachment probability
  - Expected loss (%)
  - Exhaustion probability

Risk Model
Modeling Companies

Top 10 Peril Categories



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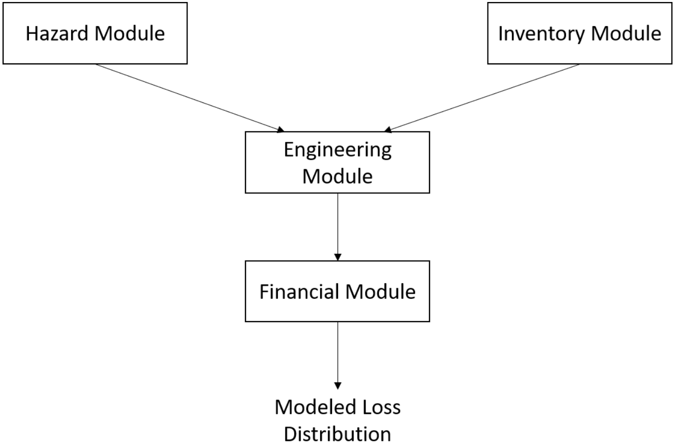
Risk Model



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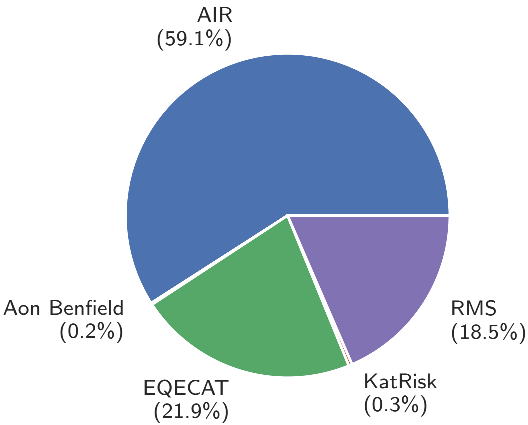
Market Share of Risk Modeling Companies



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Macro effects of natural disasters

Estimate impulse response to natural disasters with Jordà (2005) local projections:

$$\Delta_h y_{i,t+h} = \gamma_i + \gamma_t + b_1 Small_{i,t} + b_2 Large_{i,t} + \varepsilon_{i,t}$$

- 13 countries (i)
- Annual sample from 1950 to 2016 (t)
- $Small_{i,t} = 1$ if $dmg/gdp_{i,t-1} \in [0.2\%, 1\%]$ (8% of obs)
- $Large_{i,t} = 1$ if $dmg/gdp_{i,t-1} > 1\%$ (2% of obs)

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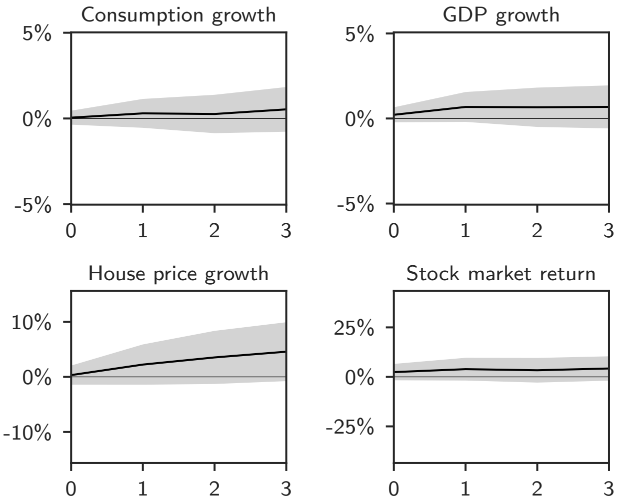
Impulse responses to small disasters



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Model

- Follows Gabaix, Krishnamurthy, Vigneron (2007)
- Two periods
- Large mass of outside investors
  - Marginal rate of substitution M_H is independent of natural disasters
- Specialized cat bond fund managers
  - Choose a portfolio of cat bonds at $t = 0$
  - Have mean-variance preferences
- Friction: Managers must contribute α% of funds they manage ("skin in the game")

Assets

Back

Model: Assets

- At $t = 0$, N cat bonds are issued at par
- Per-unit coupon of $C_i = r + s_i$ at maturity $(t = 1)$
- Bond can trigger due to natural disaster. Value of principal at maturity is:

$$P_i(x_i) = \begin{cases} 1 & x_i > \bar{x}_i \\ F_i(x_i) & \underline{x}_i \leq x_i \leq \bar{x}_i \\ 0 & x_i < \underline{x}_i \end{cases} \tag{3}$$

- Expected loss: $el_i = 1 - E_0\left(P_i\right)$
- Expected excess return: $E_0\left(R_i^e\right) = s_i - el_i$

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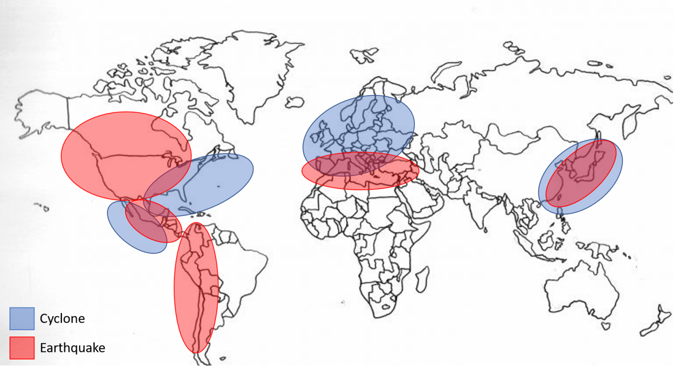
Estimating betas



- Assumption: events are uncorrelated across peril categories and perfectly correlated within categories
- Only single-peril bonds are included in the sample

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Details

Estimating betas (cont'd)

Table: Summary of Simulation Results

Variable	N	Mean	St Dev	Min	25%	50%	75%	Max
β_{sheet}	2,158	1.04	0.71	0.01	0.42	0.92	1.54	3.28
β_{trace}	1,267	0.98	0.69	0.01	0.36	0.86	1.53	2.94
N_{trials}	500,000							
N_{perils}	9							

Examples of estimated betas

Bond	Sponsor	Expected Loss	$\hat{\beta}$
Ursa Re Series 2017-1 Class E	California Earthquake Authority	3.33%	2.24
Ursa Re Series 2017-1 Class B	California Earthquake Authority	1.11%	1.28
Bosphorus Ltd. Series 2015-1 Class A	Turkish Catastrophe Insurance Pool	1.47%	0.08

Estimating betas

- Let $x_{i,t} \sim U(0,1)$. Given Attachment probability ($\bar{x}_i$), Expected loss (el_i) and Exhaustion probability ($\underline{x}_i$), I assume the following payoff function for principal:

$$P_i(x_i) = \begin{cases} 1, & x_i \geq \bar{x}_i \\ \left(\frac{x_i - \underline{x}_i}{\bar{x}_i - \underline{x}_i}\right)^{\phi_i}, & \underline{x}_i < x_i < \bar{x}_i \\ 0, & x_i \leq \underline{x}_i \end{cases} \tag{4}$$

- where $\phi_i = \frac{\bar{x}_i - \underline{x}_i}{\bar{x}_i - el_i} - 1$

- Excess return in state x then is:

$$R^e_{i,t+1}(x) = (1 + r_t + s_{i,t})P_i(x) - r_t \tag{5}$$

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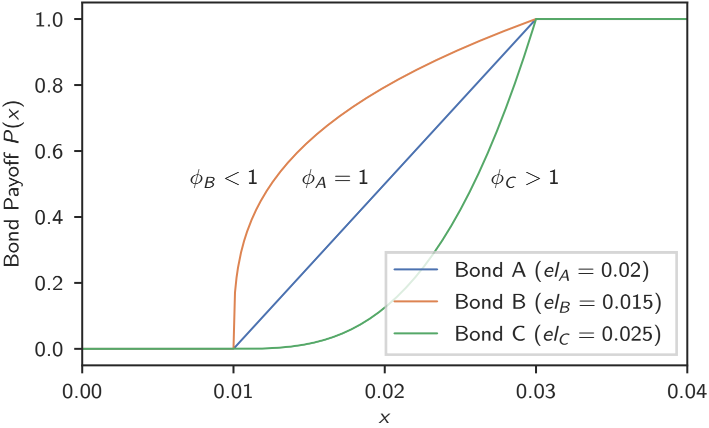
Illustration of P

Illustration of payoff function P



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Results (TRACE prices)

Table: Pricing of Catastrophe Market Risk

t	$\lambda_{0,t}$	(t-stat)	$\lambda_{cat,t}$	(t-stat)	$\lambda_{cat,t} - E_t\left(R^e_{cat,t+1}\right)$	(t-stat)	R^2	N	$N_{clusters}$
2005	0.76	1.75	**1.20**	3.39	-0.80	-2.26	0.40	16	12
2006	-1.93	-2.56	**7.57**	11.71	**1.99**	3.08	0.87	29	15
2007	**1.52**	5.32	**3.59**	9.58	**-1.32**	-3.53	0.87	23	17
2008	1.82	1.94	**2.41**	3.38	-1.35	-1.89	0.53	18	15
2009	**4.36**	4.21	**3.61**	3.26	**-3.60**	-3.24	0.53	19	15
2010	**3.47**	7.52	**1.40**	3.79	**-3.23**	-8.72	0.38	26	19
2011	1.29	1.48	**2.52**	3.51	-1.44	-2.00	0.60	18	12
2012	**1.97**	5.17	**4.14**	11.72	**-2.49**	-7.05	0.86	22	20
2013	**0.95**	4.98	**2.14**	8.40	**-1.26**	-4.95	0.76	30	26
2014	**1.36**	9.88	**0.96**	5.08	**-1.63**	-8.64	0.47	34	28
2015	**1.37**	7.47	**0.99**	6.37	**-1.41**	-9.03	0.55	35	27
2016	**0.98**	6.34	**0.91**	4.46	**-0.83**	-4.04	0.55	29	23
2017	**0.82**	3.27	0.77	2.42	-0.41	-1.29	0.14	35	27
2018	**0.72**	3.30	0.46	2.44	**-0.57**	-3.02	0.17	31	22
FM	**1.51**	9.32	**1.95**	10.02	**-1.40**	-9.47	0.46	57	

$$E_t(R^e_{i,t+1}) = \lambda_{0,t} + \lambda_{cat,t}\hat{\beta}_{i,t} + \varepsilon_{i,t+1}$$

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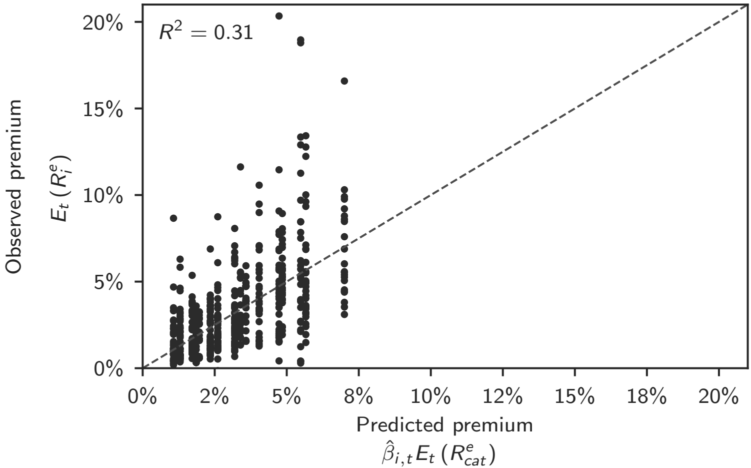
Main results



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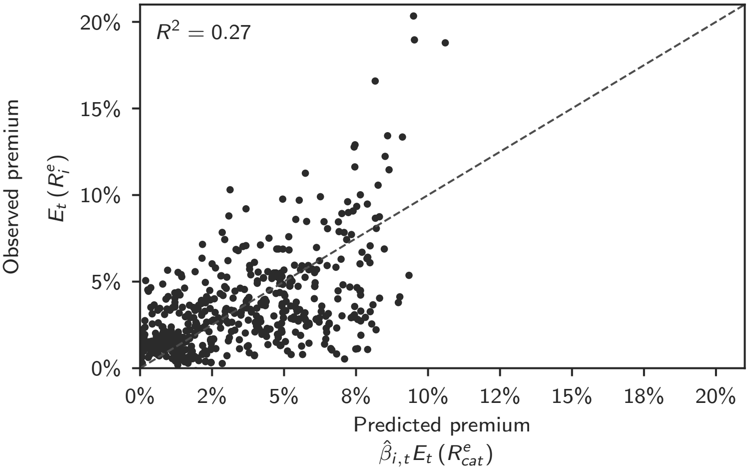
Main results



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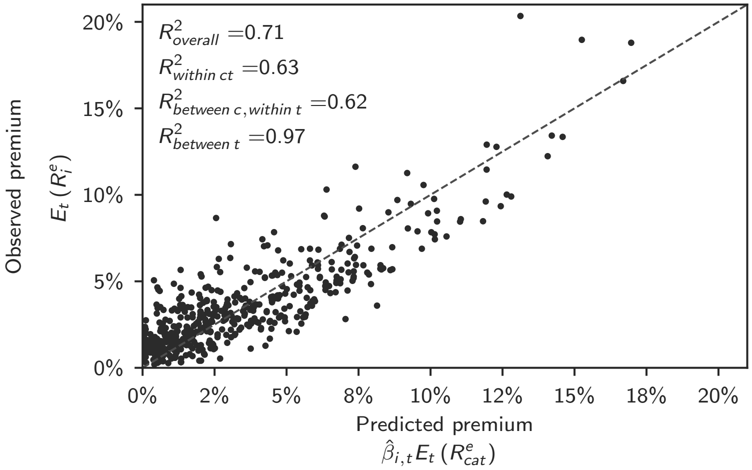
Main results



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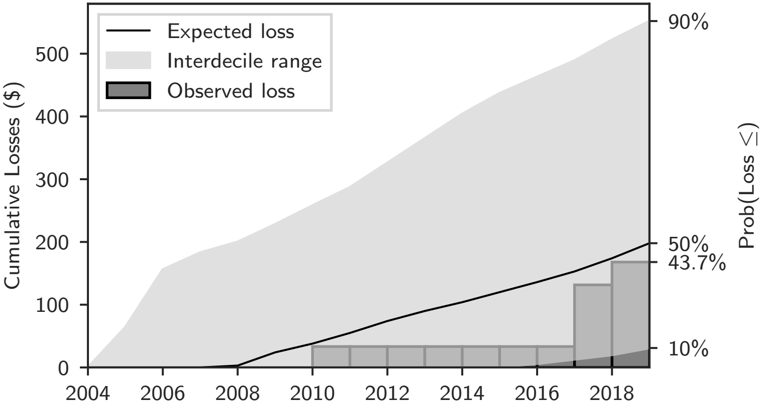
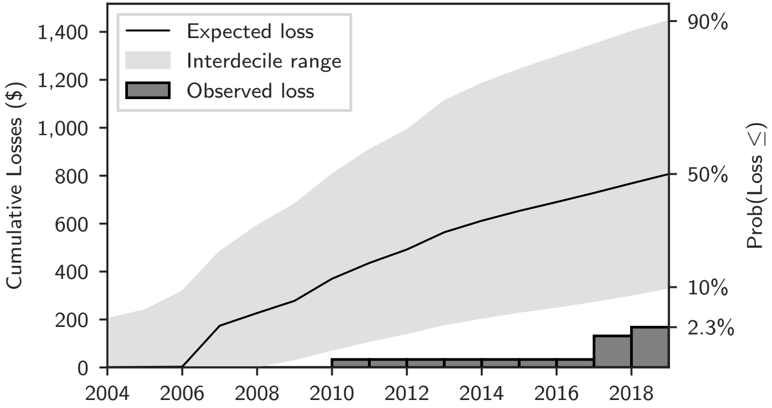
Realized losses highly consistent with the predictions of the actuarial models



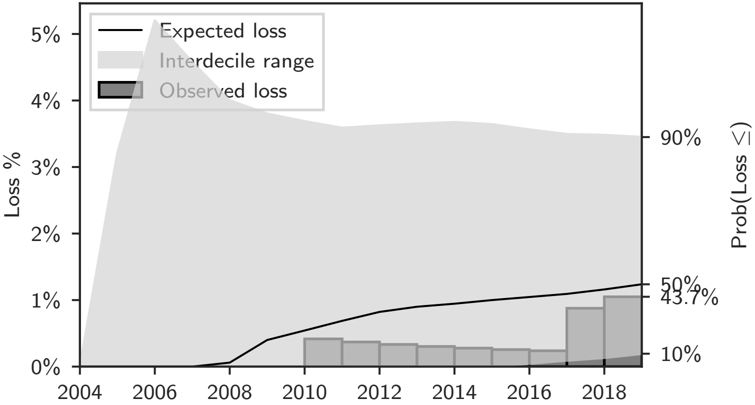
Loss %

Alternative hypothesis that all premium is due to biased loss estimates inconsistent with the data



Loss %

Modeled vs. actual losses



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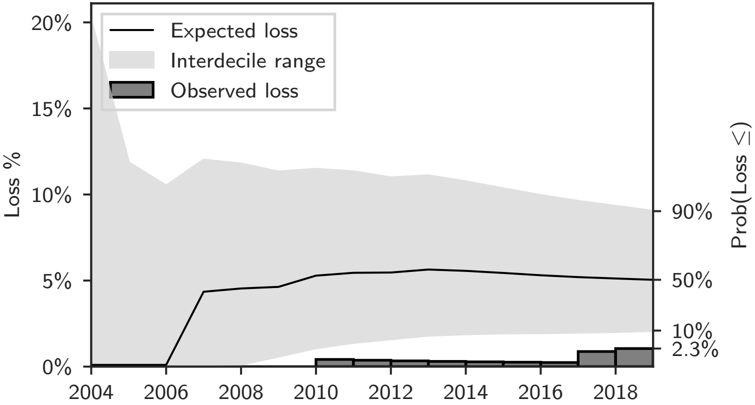
Modeled vs. actual losses (biased estimates)



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Measuring Liquidity

I use all feasible measures from Friewald, Jankowitsch, and Subrahmanyam (2012):

- Trading activity variables
  - Turnover
  - Number of trades
  - Trading interval
- Bond characteristics
  - Amount issued
  - Age
  - Time to maturity

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Measuring Liquidity (Cont'd)

Table: Correlation of Beta and Liquidity Measures

	$\hat{\beta}$	Turnover	N trades	Trading interval	Amount issued	Age	Maturity
$\hat{\beta}$	1.00	0.06	0.03	-0.04	-0.01	-0.15	-0.14
Turnover	0.06	1.00	0.65	-0.10	0.04	-0.10	0.13
N trades	0.03	0.65	1.00	-0.25	0.44	-0.11	0.15
Trading interval	-0.04	-0.10	-0.25	1.00	-0.21	0.31	-0.18
Amount issued	-0.01	0.04	0.44	-0.21	1.00	-0.04	0.12
Age	-0.15	-0.10	-0.11	0.31	-0.04	1.00	-0.57
Maturity	-0.14	0.13	0.15	-0.18	0.12	-0.57	1.00

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Liquidity: Pricing Results

Table: Pricing of Catastrophe Market Risk (Liquidity)

	Liquidity measure (LIQ)					
	Turnover	N trades	Trading interval	Amount issued	Age	Maturity
λ_0	**1.44**	**1.47**	**1.45**	**1.62**	**1.61**	**1.32**
(t-stat)	(9.45)	(9.41)	(9.12)	(8.70)	(9.67)	(5.88)
λ_{cat}	**2.03**	**2.06**	**1.81**	**2.08**	**1.99**	**2.00**
(t-stat)	(10.07)	(10.51)	(10.35)	(10.49)	(10.07)	(10.26)
λ_{liq}	-0.27	**-0.04**	-0.00	**-0.00**	**-0.17**	0.03
(t-stat)	(-2.30)	(-3.69)	(-0.99)	(-3.98)	(-3.18)	(0.54)
N	57	57	57	57	57	57
R^2	0.54	0.54	0.53	0.55	0.54	0.54

$$E_t(R^e_{i,t+1}) = \lambda_{0,t} + \lambda_{cat,t}\hat{\beta}_{i,t} + \lambda_{liq,t} LIQ_{i,t} + \varepsilon_{i,t+1}$$

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Results (Subsamples)

Table: Pricing of Catastrophe Market Risk (Subsamples)

	Main	Noncallables	Earthquake	Parametric
$\lambda_{0,t}$	**1.23**	**1.20**	**1.50**	**1.28**
(t-stat)	(9.41)	(9.53)	(8.50)	(8.82)
$\lambda_{cat,t}$	**2.06**	**2.11**	**1.98**	**1.94**
(t-stat)	(11.67)	(11.56)	(6.52)	(7.62)
$\lambda_{cat,t} - E_t\left(R^e_{cat,t+1}\right)$	**-1.10**	**-1.05**	**-1.18**	**-1.23**
(t-stat)	(-9.02)	(-8.70)	(-3.94)	(-6.51)
N	63	63	63	63
R^2	0.49	0.51	0.43	0.49

$$E_t(R^e_{i,t+1}) = \lambda_{0,t} + \lambda_{cat,t}\hat{\beta}_{i,t} + \varepsilon_{i,t+1}$$

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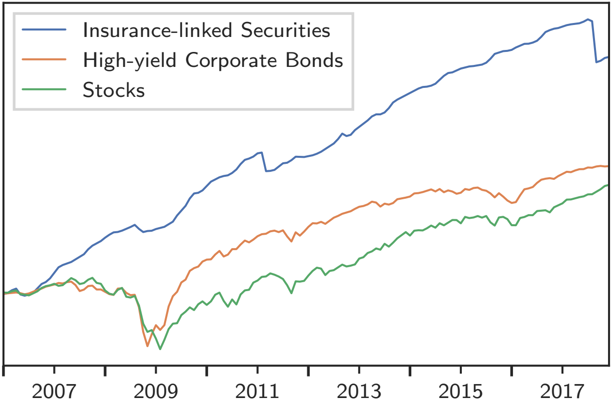
Past returns



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Accounting for Peso Problem

- SDF: $M(x_{t+1}, z_{t+1})$
- Two bonds, A and B:

$$\underline{x}_A \leq \underline{x}_B, el_A < el_B$$

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Accounting for Peso Problem (cont'd)

Assumption 1: $M(x_{t+1}, z_{t+1}) = M(z_{t+1})\,,\ x_{t+1} \geq x^*$
(Small disasters are not priced)

Assumption 2: $\underline{x}_A \geq x^*$
(Safe bond exhausts before "severe disaster threshold" is hit)

Prediction:

$$\Delta s_t = \Delta el_t$$

Empirical specification:

$$\Delta s_{i,j} = \lambda \Delta el_{i,j} + \varepsilon_{i,j}$$

H0: $\lambda = 1$

Illustration

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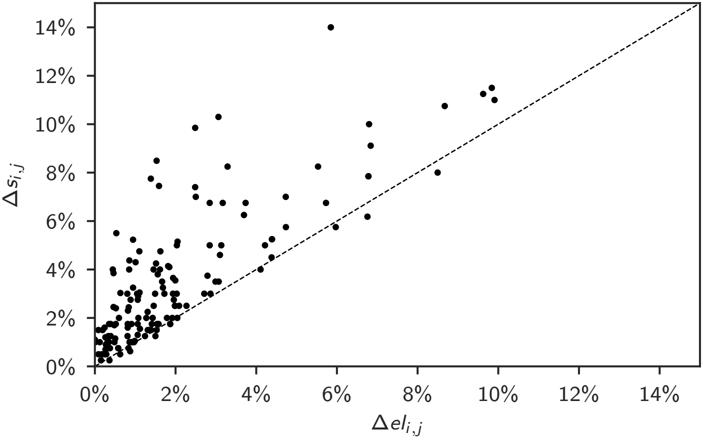
Results



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Results (cont'd)

Table: Price of non-extreme cat risk

	(1)	(2)	(3)	(4)	(5)	(6)
λ	1.46***	1.42***	1.48***	1.44***	1.44***	1.49**
	(0.09)	(0.09)	(0.12)	(0.13)	(0.15)	(0.19)
N	151	125	92	57	45	34
N Clusters	106	89	67	42	33	25
Largest Cluster (%)	2.65	3.20	4.35	7.02	8.89	11.76
R^2	0.82	0.84	0.85	0.86	0.86	0.87
Min(el_A)	0.00	0.50	1.00	1.50	2.00	2.50

$$\Delta s_{i,j} = \lambda \Delta el_{i,j} + \varepsilon_{i,j}$$

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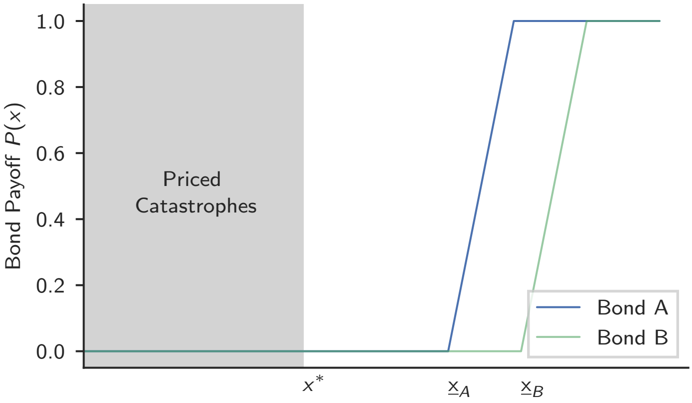
Illustration of Assumptions



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Probability Weighting

- Barberis and Huang (2008) predicts that:
  - Assets with negative skewness (*not* coskewness) have high excess returns
  - One group of investors buy all all assets, N groups of investors each short one asset
- Explains aggregate premium and market structure
- But: my beta measure is *positively* correlated with skewness (0.4)

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Probability Weighting: Pricing Results

Table: Pricing of Catastrophe Market Risk (Skewness)

	(1)	(2)	(3)
λ_0	**1.23**	**5.33**	**1.54**
(t-stat)	(9.41)	(12.38)	(5.42)
λ_{cat}	**2.06**		**2.03**
(t-stat)	(11.67)		(10.73)
λ_{skew}		**0.20**	0.03
(t-stat)		(7.76)	(1.80)
N	63	63	63
R^2	0.49	0.19	0.52

$$E_t(R^e_{i,t+1}) = \lambda_{0,t} + \lambda_{cat,t}\hat{\beta}_{i,t} + \lambda_{skew,t}Skew_{i,t} + \varepsilon_{i,t+1}$$

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Market Power in Primary Markets

Table: Catastrophe market risk and investor market power

Panel A: Summary statistics for primary market investors								
Variable	N	Mean	St Dev	Min	25%	50%	75%	Max
Volume/Size	148	1.00	0.01	0.96	1.00	1.00	1.00	1.05
N investors	148	26.48	14.69	1.00	17.75	22.00	30.25	81.00
Ownership HHI	148	0.14	0.10	0.03	0.09	0.12	0.17	1.00

Panel B: Pricing of catastrophe market risk and market power						
		$\hat{\beta}$			$\hat{\beta}_{proj}$	
$\hat{\lambda}_0$	1.23^{***}	2.17^{***}	1.18^{***}	0.90^{***}	2.56^{***}	0.87^{***}
	(0.24)	(0.68)	(0.26)	(0.23)	(0.35)	(0.27)
$\hat{\lambda}_{cat}$	1.12^{***}		1.10^{***}	1.39^{***}		1.38^{***}
	(0.25)		(0.34)	(0.16)		(0.16)
$\hat{\lambda}_{hhi}$		4.09	0.56		4.62^{*}	0.37
		(3.42)	(3.26)		(2.44)	(1.60)
R^2	0.47	0.06	0.47	0.56	0.06	0.56
N	45.00	45.00	45.00	136.00	136.00	136.00

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