Measuring the Climate Risk Exposure of Insurers

Hyeyoon Jung [1] Robert Engle [2] Shan Ge [2] Xuran Zeng [2]

[1]Federal Reserve Bank of New York

[2]Stern School of Business, New York University

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Motivation

Understanding the financial stability implications of climate change is important for researchers, financial institutions, and regulators, alike.

Insurance companies can be exposed to climate-related risk through their operations and their $12 trillion of financial asset holdings.

- Physical risk can affect insurers with higher-than-expected claim payouts.
- Transition risk can affect insurers' investments, e.g., in the fossil fuel industry, as economies shift to greener alternatives, stranding fossil fuel assets.

Empirical Challenges

1. Analyses based on past climate events may not effectively capture the change in the perception of risk.
    - Our methodology is market-based, allowing us to fully incorporate changes in the market's expectations.
2. Climate risk itself changes over time, and how firms, financial institutions, and market participants respond to the perceived risk also changes over time.
    - We estimate a dynamic model, allowing variations over time.
3. Data gaps and timeliness.
    - Our methodology only requires publicly available market data. Using market returns allows for constructing plausible and sufficiently severe scenarios.
    - We estimate our model on a daily basis, allowing for a timely response to rapidly changing climate risk.

This Paper

- We use a market-based approach to assess the resilience of insurance companies to climate risk.
- The methodology involves three steps:
  1. Measure the climate risk factor.
     - We construct a novel physical risk factor and test its validity in event studies.
  2. Estimate time-varying climate beta of insurers.
     - Dynamic Conditional Beta (DCB) model
  3. Compute systemic climate risk (CRISK).
     - CRISK: Expected capital shortfall of insurers in a climate stress scenario
- Use the CRISK measure to study the climate-related risk exposure of large insurance companies.

P&C Insurer Life Insurer

Key Findings

- P&C Insurers' Physical Risk Exposure
  - In a physical climate stress scenario, the top ten P&C insurers have seen either a modest capital shortfall or an excess capital reserve.

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  - Aggregate marginal transition CRISK of life insurers increased by over $70 billion (13% market cap).

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- Life Insurers' Transition Risk Exposure
  - Life insurers' transition climate beta surged amid 2019-2020 fossil fuel price collapse.
  - Aggregate marginal transition CRISK of life insurers increased by over $70 billion (13% market cap).
- Validation
  - P&C insurers with greater operational exposure to risky states have higher physical climate beta.
  - Life insurers with higher brown bond exposure have higher transition climate beta.

Physical Climate Risk Factors

Physical Climate Risk Factor

We construct a portfolio of P&C insurance company stocks specifically designed to decrease in value as physical risk escalates.

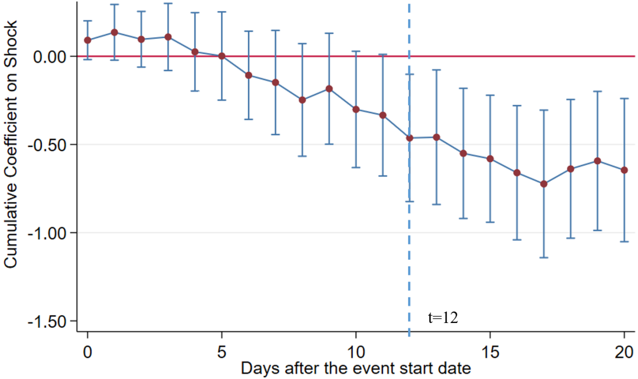
<u>**Steps**</u>:

1. Merge data on P&C insurers' direct premiums earned (DPE) + data on property damage following natural disasters from SHELDUS at the state-year level.
2. For each year, compute insurer i's realized "RISK":

$$RISK_{i,t} = \sum_{s} \left[\underbrace{\left(\frac{DPE_{i,s,t-1}}{\sum_s DPE_{i,s,t-1}} \right)}_{\text{Exposure to state } s} \times \underbrace{Property\ Damage_{s,t-1}}_{\text{Riskiness of state } s} \right] \times \frac{1}{ME_{i,t-1}}$$

3. Form a portfolio of P&C insurance company stocks, weighted by $RISK$. RBC Factor

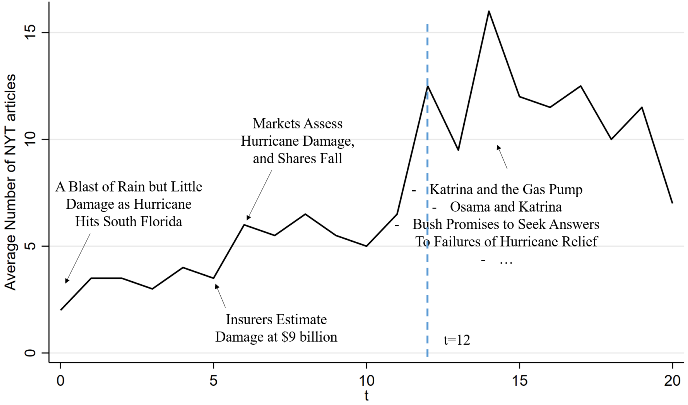
Physical Climate Risk Factor's Response to Natural Disasters



- $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$.
- $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and 0 otherwise.

RBC Factor

New York Times Articles Following Natural Disasters

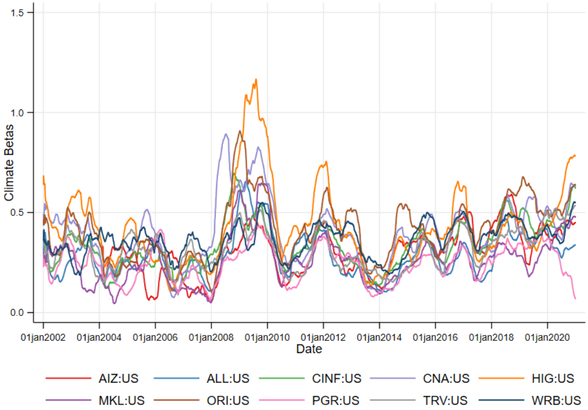


- Natural disasters' impacts are often not immediately clear.
- News articles respond to natural disasters with a few days of delay.

P&C Insurers' Physical Risk Exposure

Physical Climate Beta of US P&C Insurers

$$r_{it} = \beta_{it}^{PCF} PCF_t + \beta_{it}^{MKT} MKT_t + \varepsilon_{it}$$



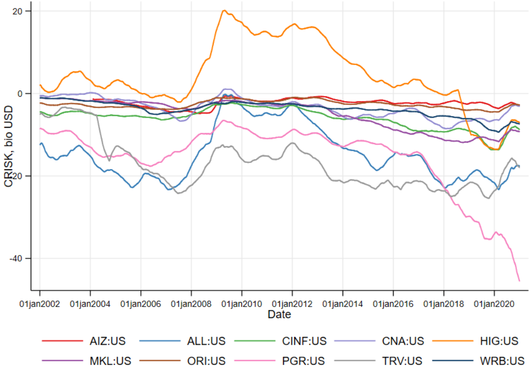
CRISK

$$\begin{aligned} CRISK_{it} &= E_t[\text{Capital Shortfall}_i \mid \text{Climate Stress}] \\ &= E_t\left[k(D_{it} + W_{it}) - W_{it} \mid \text{Climate Stress}\right] \\ &= kD_{it} - (1-k) \underbrace{(1 - LRMES_{it})}_{=\exp\left(\beta_{it}^{Climate}\log(1-\theta)\right)} W_{it} \end{aligned}$$

- D: Book value of debt
- W: Market capitalization
- LRMES: Expected equity loss conditional on the climate stress
- Prudential level of equity relative to assets $k = 0.08$ ($k = 0.055$ for Europe)
- Climate stress level $\theta = 0.2$
  - 1 percentile of 6-month return on the physical climate factor

Physical CRISK of US P&C Insurers

$$\begin{aligned} CRISK_{it} &= E_t[\text{Capital Shortfall}_i \mid \text{Climate Stress}] \\ &= kD_{it} - (1-k)(1 - LRMES_{it})W_{it} \end{aligned}$$

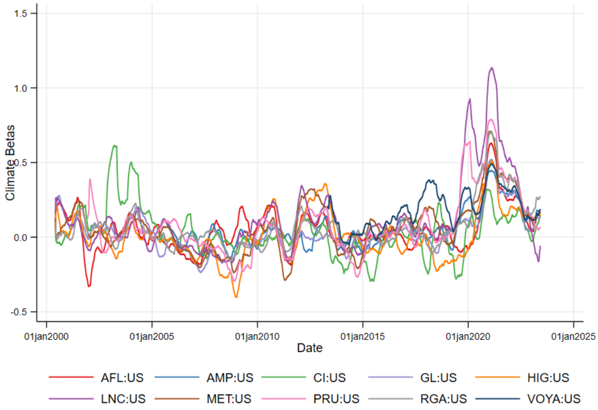


Marginal CRISK | Decomposition (2020) | Decomposition (2008) | Aggregate CRISK | Aggregate mCRISK

Life Insurers' Transition Risk Exposure

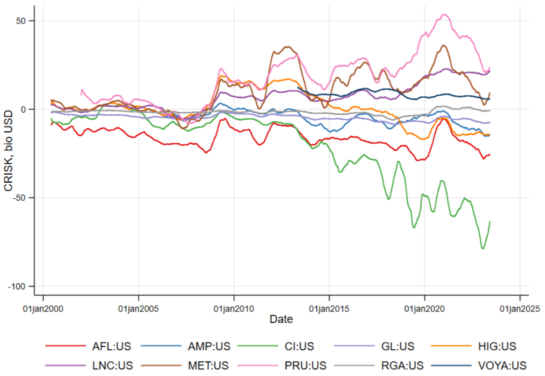
Transition Climate Beta of US Life Insurers

$$r_{it} = \beta_{it}^{TCF} TCF_t + \beta_{it}^{MKT} MKT_t + \varepsilon_{it}$$



Transition CRISK of US Life Insurers

$$CRISK_{it} = E_t[\text{Capital Shortfall}_i \mid \text{Climate Stress}]$$
$$= kD_{it} - (1-k)(1 - \textcolor{red}{LRMES_{it}})W_{it}$$



Marginal CRISK | Decomposition (2020) | Aggregate CRISK | Aggregate mCRISK

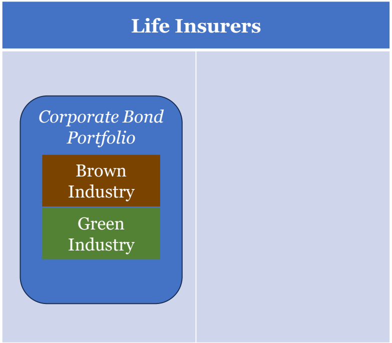
Validation

Life Insurers' Corporate Bond Portfolio Beta

For each industry j equities:

$$r_{jt} = \alpha + \beta_{jt}^{TCF} TCF_t + \beta_{jt}^{MKT} MKT_t + \varepsilon_{jt}$$

$$\text{Bond portfolio beta}_t = \sum_j w_{jt} \beta_{jt}^{TCF}$$



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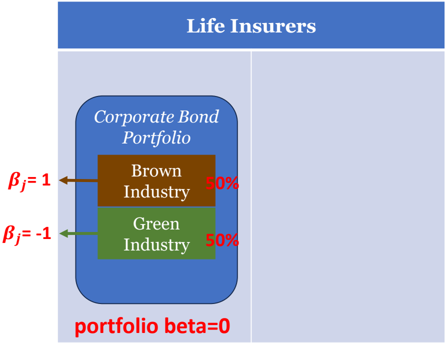
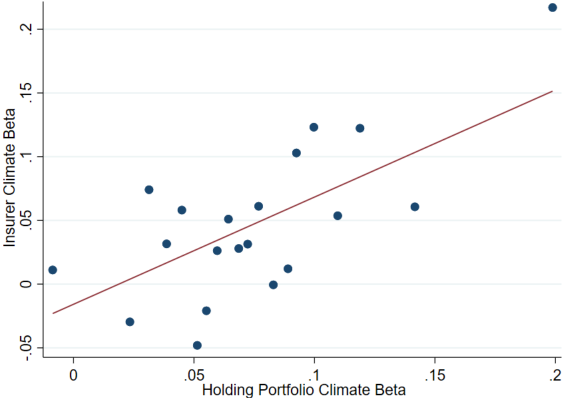


Life Insurers' Corporate Bond Portfolio



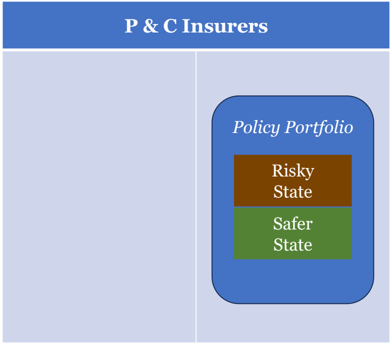
- Insurers' asset holding data (Schedule D Part 1 of the Annual statement), 16 insurers, 2000-2020
- Life insurer transition climate beta reflects corporate bond portfolio exposure to transition risk.

Life Insurers' Corporate Bond Portfolio

	(1) Climate Beta	(2) Climate Beta
Bond Portfolio Climate Beta	0.950***	1.090***
	(0.236)	(0.225)
Size		-0.012
		(0.008)
Leverage		0.006***
		(0.001)
N	292	292
R^2	7.57	23.2

- $\beta_{it}^{Transition} = a + b$ Bond Portfolio Transition Climate Beta$_{it}$ + Insurer Controls + ε_{it}

P&C Insurers' Policy Portfolio Beta



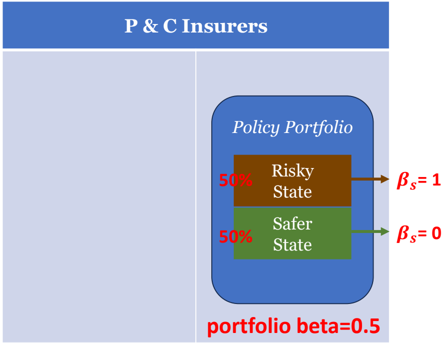
For each county c municipal bonds:

$$r_{ct} = \alpha + \beta_{ct}^{PCF} PCF_t + \beta_{ct}^{MKT} MKT_t + \varepsilon_{ct}$$

For each state, take the 99 pct β_{ct}^{PCF} as β_{st}^{PCF}

Policy portfolio beta$_t = \sum_s w_{st} \beta_{st}^{PCF}$

P&C Insurers' Policy Portfolio Beta



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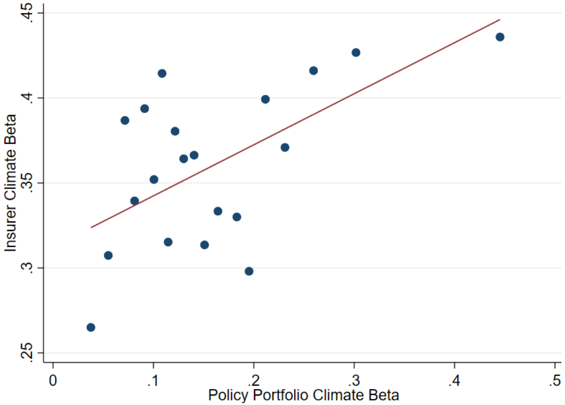
Policy portfolio beta$_t = \sum_s w_{st} \beta_{st}^{PCF}$

P&C Insurers' Policy (Operation) Portfolio



- Based on insurers' operation (NAIC and SNL) and municipal bond (Mergent and MSRB) data, 21 insurers, 2000-2020 Munis Data Munis Return
- P&C insurer physical climate beta reflects their policy portfolio exposure to physical risk.

P&C Insurers' Policy (Operation) Portfolio

	(1) Climate Beta	(2) Climate Beta
Policy Portfolio Climate Beta	0.152***	0.106**
	(0.043)	(0.043)
Size		-0.037***
		(0.008)
Leverage		0.010***
		(0.002)
N	279	279
R^2	2.80	13.9

- $\beta_{it}^{Physical} = a + b$ Policy Portfolio Climate Beta$_{it}$ + Insurer Controls + ε_{it}

Conclusion

- We measure climate risk exposure of life and P&C insurance companies in the U.S. using a market-based approach.
- Large P&C insurers have relatively low physical CRISK.
- The aggregate marginal transition CRISK of life insurers increased by over $70 billion following the collapse in fossil fuel prices during 2019-2020.

- Market-based physical climate beta reflects P&C insurers' policy portfolio composition.
- Market-based transition climate beta reflects life insurers' bond portfolio composition.

Appendix

Insurers Characteristics & Climate Risk

Top 10 P&C Insurer Summary Statistics

Ticker	Insurer	Mktcap	Asset	Equity	DPE Share(%)	HHI
ALL	Allstate	10.17	11.74	9.93	29.21	0.066
TRV	Travelers	10.10	11.40	9.88	15.76	0.049
PGR	Progressive	9.79	10.07	8.79	3.92	0.157
HIG	Hartford	9.64	12.24	9.63	27.45	0.051
CNA	CNA Financial	9.02	10.99	9.28	25.24	0.049
CINF	Cincinnati Financial	8.97	9.76	8.75	3.61	0.082
MKL	Markel	8.58	9.58	8.17	27.70	0.050
AIZ	Assurant	8.52	10.30	8.43	26.02	0.053
WRB	WR Berkley	8.51	9.67	8.10	8.77	0.045
ORI	Old Republic	8.31	9.55	8.30	18.40	0.122

- Top ten P&C insurers collect approximately 18.6% of their premiums in risky states.
- There is significant variation among insurers (3.6& - 29.2%)
- Insurers' operational exposures are well diversified across states.

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P&C Insurers' Policy Portfolio Exposure to Physical Risk

- **DPE Share** measures insurer's exposure to risky states

$$DPE\ Share_{i,t} = \frac{\text{Direct Premiums Earned (DPE) in California, Florida, Texas}_{i,t}}{\text{Total DPE}_{i,t}}$$

  Risky states are identified in terms of the average annual property damage caused by all hazards.

- **HHI** measures the degree of each insurer's operational portfolio diversification:

$$HHI_{i,t} = \sum_{j \in J} (\text{DPE Exposure}_{i,j,t})^2$$

  where j denotes state.

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Top 10 Life Insurer Summary Statistics

Ticker	Insurer	Mktcap	Asset	Equity	Brown Share(%)	Brown Exposure(%)
MET	MetLife	10.52	13.25	10.61	17.20	4.74
PRU	Prudential	10.32	13.26	10.40	13.72	4.36
AFL	Aflac	10.08	11.37	9.38	11.83	4.48
CI	Cigna	9.86	11.11	9.09	13.99	4.34
HIG	Hartford	9.64	12.24	9.63	11.86	4.20
AMP	Ameriprise	9.62	11.78	8.96	18.34	5.21
LNC	Lincoln National	9.19	12.14	9.30	15.59	4.66
VOYA	Voya Financial	8.95	12.19	9.39	12.56	4.53
GL	Globe	8.70	9.76	8.28	19.46	5.17
RGA	Reinsurance	8.30	10.20	8.29	12.74	4.39

- 14.7% of life insurers' corporate bond portfolio is exposed to the brown industry.
- 4.6% of corporate bond portfolio to be lost under a severe carbon tax scenario.
- The brown exposure estimates are similar to large US banks (3-4%) by Jung et al. (2023)

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Corporate Bond Portfolio Exposure to Transition Risk

- Brown Share:

$$Brown\ Share_{i,t} = \frac{Brown\ Industry\ CorporateBonds_{i,t}}{Corporate\ Bonds_{i,t}}$$

- Brown Exposure:

$$Brown\ Exposure_{i,t} = \sum_{j \in J} w_{i,j,t}\ Markdown_j,$$

  - w_{ijt} is proportion of insurer i's corporate bond invested in industry j at time t
  - $Markdown_j^P$ is the drop in the output of industry j under carbon tax ($50 growing at 5% annually)
  - **Key Assumptions:**
    1. Insurers lose the value of loans proportionally to the drop in the output of the borrower's industry.
    2. Insurer i maintains their allocation of corporate bonds across industries as of time t.

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Insurer RBC Factor

Listed P&C Insurers (NAIC & SNL) + CRSP/Compustat

- Idea: $RBC = Equity/Required\ Equity$
- Inverse the above to measure the "riskiness" for each insurer i:

$$RISK_{i,t} = \frac{1}{RBC_{i,t}} = \frac{Required\ Equity_{i,t}}{Equity_{i,t}} = \frac{\sum_j \bar{\rho}_{i,j,t-1} DPE_{i,j,t-1}}{ME_{i,t-1}}$$

where ρ is "risk weights":

$$\rho_{i,j,t} = \frac{Loss_{i,j,t}}{DPE_{i,j,t}}$$

and $\bar{\rho}$ is smoothed risk weights:

$$\bar{\rho}_{i,j,t} = \sum_{s=1}^{k} \rho_{i,j,t-s}\ \delta^s$$

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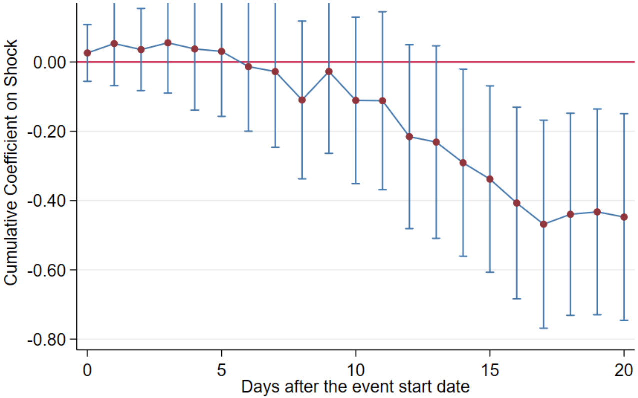
Insurer RBC Factor's Response to Natural Disasters



- $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$.
- $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. PCF_t: physical risk factor. MKT_t: market factor (SPY).

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Factor Summary Stats

	Mean	St.Dev.	25th percentile	75th percentile	Count
Market (SPY)	0.0003	0.0123	-0.0041	0.0058	4784
PCF: Insurer Premium	0.0006	0.0170	-0.0072	0.0079	4784
PCF: Loss-to-Equity	0.0005	0.0163	-0.0063	0.0073	4784
TCF: Stranded Asset	-0.0005	0.0134	-0.0070	0.0068	4784

Table: **Summary Statistics of Factors** The sample period is 2002-2020 and all factors are daily.

Factor Correlation

	(1)	(2)	(3)	(4)
(1) Market: SPY	1.00			
(2) PCF: Insurer Premium	0.74	1.00		
(3) PCF: Loss-to-Equity	0.78	0.90	1.00	
(4) TCF: Stranded Factor	0.22	0.19	0.18	1.00

Table: **Correlation of Factors** The sample period is 2002-2020 and all factors are daily.

6-Month Cumulative Returns

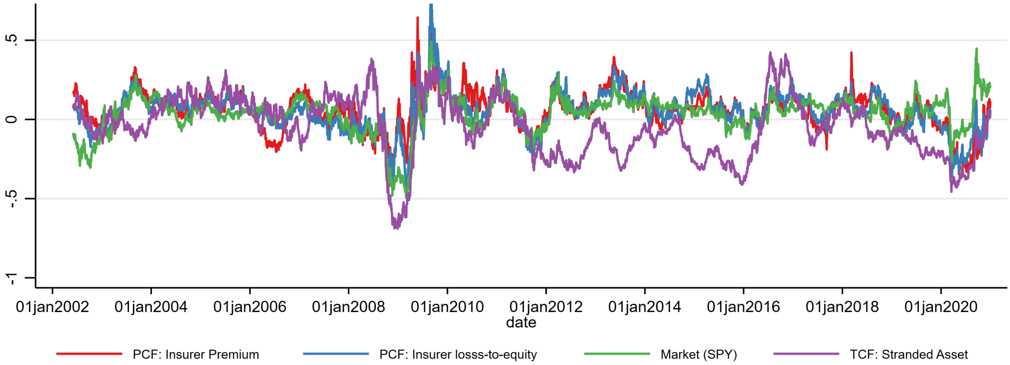
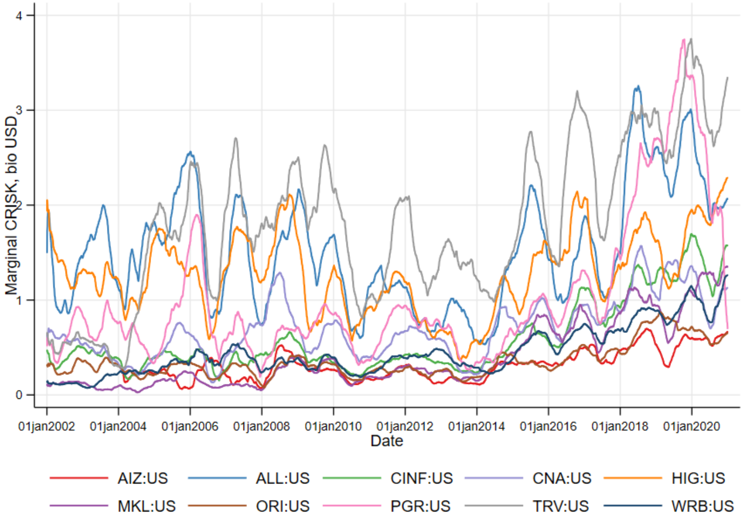


Figure: **6-Month Cumulative Returns**

Physical Marginal CRISK of US P&C Insurers



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Physical CRISK Decomposition (end of 2020)

Ticker	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
PGR	-31.85	-51.55	-19.70	0.39	-13.86	-6.23
TRV	-22.79	-22.05	0.75	0.31	-0.17	0.61
ALL	-22.94	-21.25	1.69	0.04	2.56	-0.91
HIG	-13.75	-9.43	4.32	0.03	3.51	0.79
MKL	-11.30	-9.58	1.73	0.11	1.30	0.32
CINF	-12.81	-10.16	2.65	0.10	2.55	-0.00
WRB	-8.81	-7.95	0.86	0.16	0.70	0.00
CNA	-5.89	-4.64	1.25	0.19	1.29	-0.24
AIZ	-3.57	-3.74	-0.17	-0.03	-0.05	-0.09
ORI	-4.08	-3.51	0.57	0.06	0.63	-0.12
Top 10			-19.42	1.37	-3.40	-17.38

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Physical CRISK Decomposition (end of 2008)

Ticker	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
TRV	-23.15	-15.02	8.14	-0.34	7.02	1.46
ALL	-15.92	-3.81	12.10	-0.99	10.22	2.87
PGR	-10.90	-7.41	3.48	0.01	2.95	0.52
WRB	-3.84	-3.13	0.71	-0.01	0.40	0.32
HIG	3.06	18.53	15.47	-5.03	18.41	2.09
CINF	-4.85	-3.20	1.65	-0.12	1.57	0.20
CNA	-4.25	0.01	4.26	-0.15	3.95	0.46
AIZ	-5.32	-1.31	4.01	-0.15	3.81	0.35
MKL	-3.79	-1.82	1.96	-0.01	1.68	0.29
ORI	-2.49	-1.36	1.13	0.06	0.67	0.40
Top 10	.	.	52.92	-6.73	50.67	8.97

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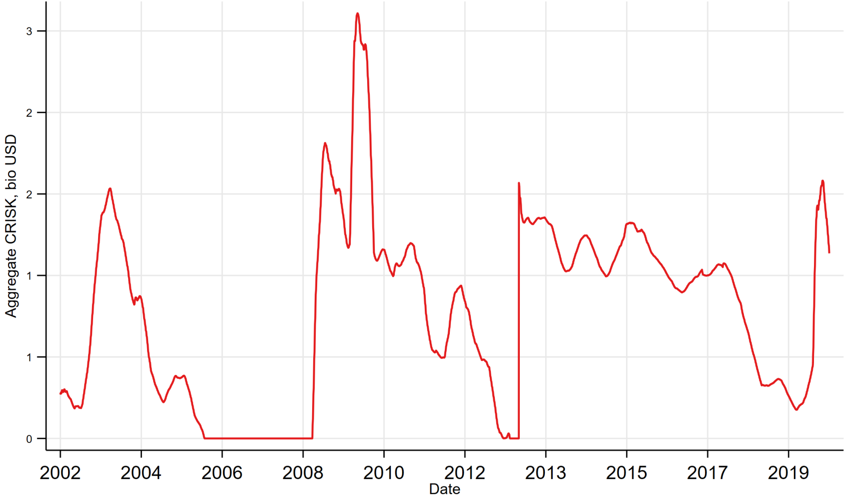
Aggregate Physical CRISK



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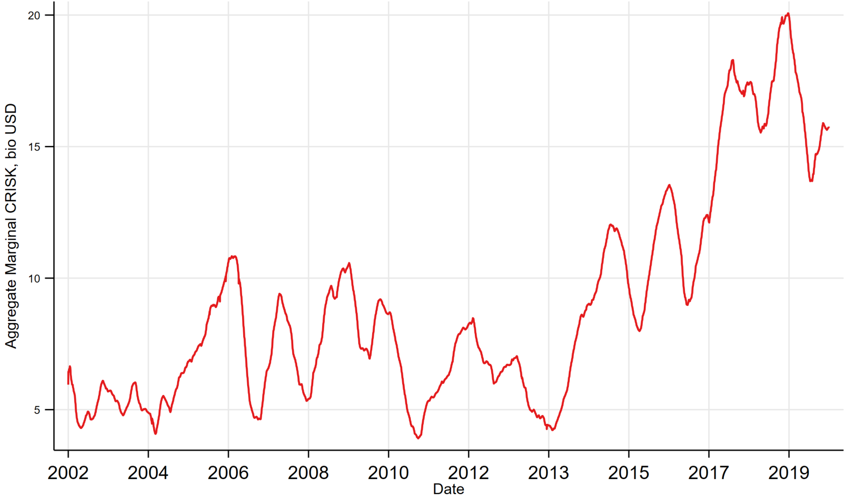
Aggregate Physical mCRISK



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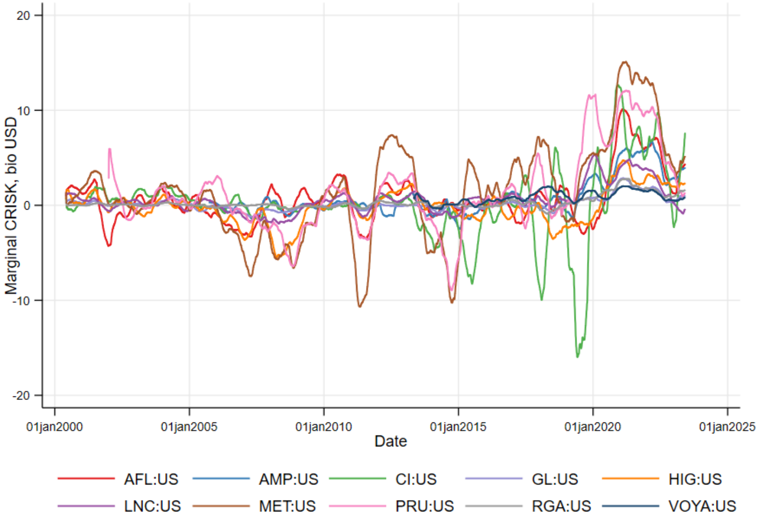
Transition Marginal CRISK of US Life Insurers



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Transition CRISK Decomposition (end of 2020)

Ticker	CRISK(t-1)	CRISK(t)	dCRISK	dDEBT	dEQUITY	dRISK
CI	-59.99	-59.47	0.51	0.15	1.04	-0.68
MET	15.50	30.09	14.59	2.62	3.34	8.63
AFL	-30.84	-9.40	21.44	0.30	6.38	14.75
PRU	37.01	49.98	12.97	2.03	4.49	6.46
AMP	-5.66	-3.85	1.81	0.66	-1.38	2.52
HIG	-14.66	-6.91	7.74	0.03	3.28	4.43
GL	-8.36	-4.97	3.39	0.11	1.11	2.17
LNC	18.35	21.80	3.45	1.68	0.95	0.82
RGA:US	-3.61	1.14	4.75	0.37	1.65	2.73
VOYA	5.99	7.90	1.92	0.41	0.58	0.92
Top 10			72.57	8.36	21.45	42.76

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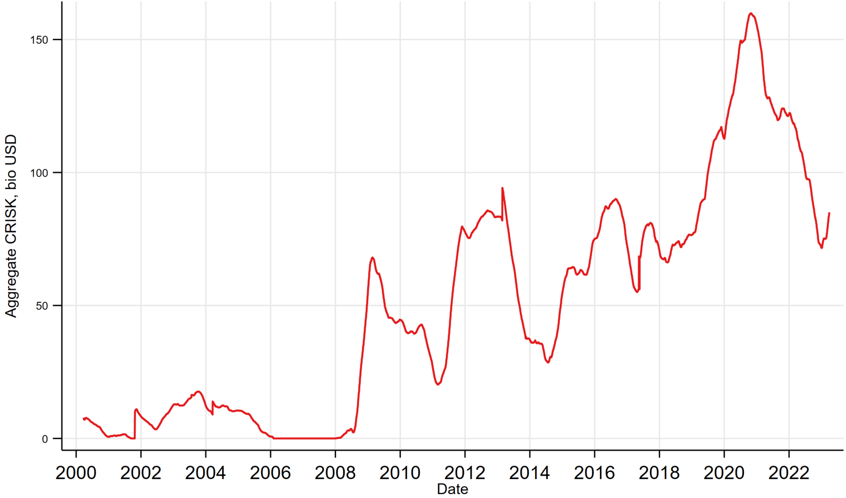
Aggregate Transition CRISK



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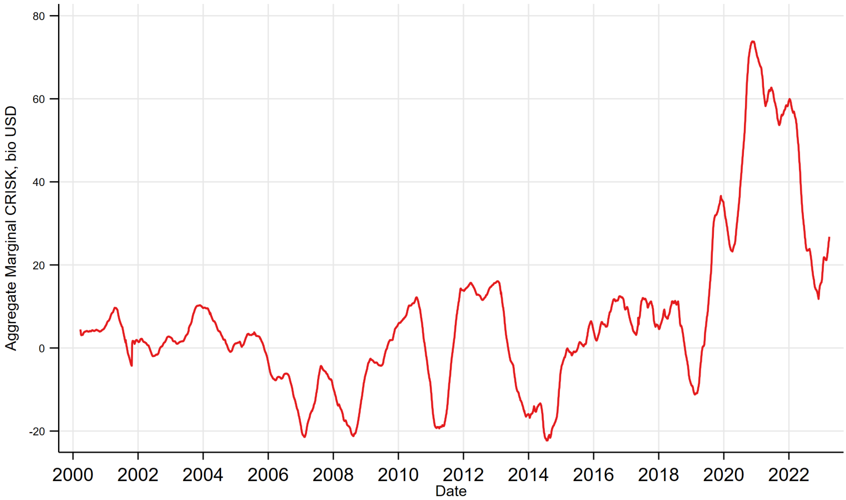
Aggregate Transition mCRISK



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Municipal Bonds Data

We include the municipal bonds satisfying Acharya et al. (2022):

- Fixed-coupon, tax-exempt, with no insurance (issuer-specific credit risk)
- With more than 10 trade observations (illiquidity)
- With time to maturity of fewer than 100 years, coupon rate less than 20%, and a price between \$50 and \$150 on a \$100 notional (data errors)
- Our final sample includes 150,666 bonds issued by 1,386 counties, with price data covering January 2005 through June 2022.

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Municipal Bonds Return Estimation

Estimation of the monthly return is based on repeat-sales models (Auh et al. 2022):

- $R_{i,b:s} = \sum_{t=b+1}^{s} R_t^c + e_{i,b:s}$, where $R_{i,b:s} = log(p_{i,s}/p_{i,b})$, $R_t^c = log(1 + r_t^c)$. $p_{i,s}$ and $p_{i,b}$ are prices of bond i in months s and b ($s > b$) respectively. r_t^c denotes the monthly return in county c and month t. $e_{i,b:s}$ represents the bond-specific idiosyncratic return component.
- The monthly return R_t^c is estimated in panel regressions as the coefficient on the monthly indicator variables. Each $b - s$ monthly indicator variable is equal to one in the one month that falls between $b + 1$ and s and is equal to zero in all other months.
- We use weighted least squares regressions with the weight being the square root of issue amounts divided by the square root of the time interval between b and s.

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