Physical Climate Risk Factors and an Application to Measuring Insurers' Climate Risk Exposure

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July 26, 2024

Abstract

We construct a novel physical risk factor by forming a portfolio of property and casualty (P&C) insurers' stocks, with each insurer's weight reflecting their operational exposure to states with high physical climate risk. Insurance companies can be exposed to climate-related physical risk through their operations and transition risk through their \$12 trillion of financial asset holdings. We assess the climate risk exposure of P&C and life insurance companies in the U.S. We estimate insurers' dynamic *physical climate beta*, i.e. their stock return sensitivity to the physical risk factor. In addition, we calculate the expected capital shortfall of insurers under various climate stress scenarios. Validating our approach, we find that insurers with larger exposures to risky states have a higher sensitivity to physical risk, while insurers holding more brown assets have a higher sensitivity to transition risk.

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The views expressed in this paper are those of the author(s) and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. We thank Ana-Maria Tenekedjieva, Shaojun Zhang, Emilia Garcia-Appendini, Katherine Wagner, Celso Brunetti, Simon Rother, Ralph Koijen, Stefano Giglio, Harrison Hong, Caroline Flammer, Wolfram Schlenker, Douglas Almond, Johannes Stroebel, James Stock, Joao Santos, Richard Crump, Nina Boyarchenko, Viral Acharya, Jeffrey Wurgler, Lee Seltzer, and participants at the Econ Summit, Federal Reserve System Banking Conference, Financial Stability Conference, Annual Conference of the Central Bank of Chile, NY Fed seminar, Federal Reserve Board seminar, Columbia University seminar, Midwest Financial Association Meeting, CESifo Conference on Energy and Climate Economics, ZEW Conference on Ageing and Sustainability, NYU VRI Conference on Insurance and Rising Climate-Related Risks, Banca d'Italia and the IMF Conference, and Western Economic Association International Conference for their helpful comments.

1 Introduction

Climate change is increasing the frequency and severity of natural disasters, which households and businesses hedge with insurance. An important question arises: can the insurance sector withstand the stress of climate change? To answer this question, it is crucial first to understand insurers' exposure to climate risk. In addition, as important financial institutions and the largest investor group of corporate bonds, insurers' exposure to climate risk can be a key channel through which climate change risk can threaten broader financial stability. In this paper, we assess insurers' exposure to climate risk through their operations and their $12 trillion financial asset holdings.

On the one hand, insurers' operations can be significantly affected by physical climate risks, which stem from potential damage caused by extreme events and shifts in climate patterns. These risks can lead to unexpected claim payouts that exceed projections when the frequency and intensity of natural disasters become worse than expected. There can be a few counterarguments. First, one may argue that insurers can simply raise premiums to reflect the increased risks in these states. However, there are regulatory frictions that prevent premiums from fully reflecting the risks, especially in high-risk states (see, Oh et al. (2022)). Even if insurers can do so, higher premiums will lead to lower take-up of insurance. Wagner (2022) finds that flood insurance take-up rates dropped significantly when premiums increased, although the premiums remained substantially below the actuarial costs. With lower take-up, even if insurers can maintain the per-policy profitability, their total profits will suffer. Second, one may argue that insurers can stop operating in risky states as the physical climate risk increases. However, even if insurers can easily do so when part of their operating portfolios are no longer profitable, increased physical climate risk lowers the total profit of the exposed insurers.

On the other hand, insurers' large holdings of financial assets can be affected by both physical and transition climate risks. Physical climate events could lower the value of financial assets. For example, sea level rise or hurricanes can cause damage to coastal properties, thereby decreasing the value of mortgage bonds. Insurers' assets are also exposed to transition risk, which arises from policy, technology, and preference changes towards less carbon-intensive economies. Insurers that invest heavily in fossil fuel companies will experience a decline in asset value as these assets become "stranded" amid the shift away from fossil fuels. Therefore, physical and transition risks can affect both insurers' current and future profits, potentially leading to systemic undercapitalization of the insurance sector.

Despite its significance, our understanding of insurers' exposure to climate change risk, including both physical and transition risks, remains limited. The omission of the insurance sector in many regulatory climate stress tests is a notable concern, as highlighted by Financial Stability Board and Network of Central Banks and Supervisors for Greening the Financial System (2022).[1] A recent review conducted by Acharya et al. (2023) calls for research on the effects of climate change on insurance companies.

The first major challenge in studying insurers' exposure to climate risk lies in measuring risk, especially physical climate risk. Adequate and reliable data on climate risks are crucial for assessing insurers' exposure. However, data on future climate scenarios and projections are inherently uncertain and subject to various modeling assumptions. One approach is to use historical data to proxy for such future risks. However, the perception of physical risks can change without a direct experience of climate change events. Furthermore, climate risks are dynamic and can evolve. Climate risks may change as new hazards emerge or existing risks intensify. Insurers' exposure can also change as they change their operations, e.g., where to sell policies. Even if one can cleanly measure physical risk, it is still a challenge to measure insurers' exposure to it.

We use a novel approach to overcome these challenges in assessing insurers' climate risk exposure. We use a market-based method, relying solely on publicly available data,

[1]Out of the 35 stress testing exercises conducted by 23 jurisdictions at both country and EU levels, only one-third of the exercises incorporated the insurance sector (e.g., Bank of England, 2021; AutoritÃ© de ContrÃŽle Prudentiel et de RÃ©solution, 2020).

including those from the stock market, which tackles the challenge stemming from the lack of adequate and reliable data. Specifically, we construct several portfolios that are designed to fall in value as physical risk rises. One such portfolio uses data on US P&C insurers' premiums across states, combined with data on state-level natural disaster events. We form a portfolio of public P&C insurers where the weight is each insurer's premium exposure to the states with high past damages due to natural disasters. The costliest type of disaster in the US is hurricanes, followed by drought and wildfire. These disasters are expected to become more intense and frequent due to climate change according to many meteorological studies. We refer to the return on this portfolio as an *insurer premium physical risk factor*.[2]

Why do we assign larger weights to insurers with more exposure to states that experienced more natural disasters? States with more past exposure will also have a higher future exposure to natural disasters. Such states' (e.g. Florida and California) expected future damages are more sensitive to climate change. When the expectation of future physical climate risks becomes higher, the expected future disaster damages for such states increase by more. We argue that insurers with more operational exposure to these states are likely to experience lower returns with increased physical risk expectations. As we mentioned above, although insurers can mitigate such exposure by raising premiums and exiting risky markets, they will experience a loss of total profits even if we ignore the many frictions for these mitigation strategies.

The ideal physical risk factor should move with changes in expected physical climate risks, which are difficult to measure. Climate risks can be conceptualized as probabilities multiplied by damages related to climate change. If our factor is indeed capturing expected climate risks, then our factor should fall when some of these damages are realized (with 100% probability). Therefore, a feasible validation exercise is to test whether our fac-

[2] In addition, We propose a few other portfolios. For example, we proxy insurers' physical risk exposure based on their premiums and losses. We assign portfolio weights to each insurer based on losses relative to its market capitalization.

tors fall when climate-related natural disasters happen. We conduct event study analyses and find that the factors decline after large natural disaster events. This empirically validates the factors, as it indicates that insurers with significant exposure to states associated with high physical risk, on average, experience a decline in stock returns following severe natural disasters. Therefore, when expected physical climate risks increase, i.e., when we expect more frequent and/or severe disasters due to climate change, our factors should fall in value.

Next, we estimate insurers' stock return sensitivity to our physical risk factors, the *physical climate risk beta*. To capture the *time-varying* nature of this beta, we employ the dynamic conditional beta model proposed in Engle (2002, 2016), which addresses the challenge of the inherent uncertainties and modeling assumptions associated with future climate scenarios and projections.

We then estimate insurers' expected capital shortfall in a climate stress scenario, which we term *CRISK*, following the framework proposed by Jung et al. (2021). We choose a severe, yet plausible scenario to calibrate the stress level: the climate risk factor experiences the lowest one percentile of its six-month return distribution. By utilizing the climate beta estimates obtained in the preceding step, we estimate insurers' expected equity loss under the climate stress scenario. By integrating this estimation with key balance sheet information, including insurer size and leverage, we convert the expected equity loss into an expected capital shortfall. CRISK thus represents the shortfall in an insurer's capital from the level necessary to meet prudential capital requirements in a climate stress scenario. With this framework, we can quantitatively analyze insurance companies' exposure not only to physical risk and transition risk but also to compound risk, which refers to the combined impact of multiple stress scenarios occurring simultaneously.

While the market-based approach has many benefits, it is important to acknowledge that, by construction, our framework can capture climate change risk only to the extent that the market prices the risk. This raises a question: whether equity market investors account for climate risk. Our finding that the constructed physical risk factors respond to natural disasters suggests that the equity market prices physical climate risk. Similarly, Jung et al. (2021) document that transition factors respond to transition-related events, such as the signing of the Paris Agreement and the withdrawal from the Paris Agreement. Additionally, a growing body of literature has found evidence that physical climate risk is priced in the financial market. For example, in the equity market, Acharya et al. (2022) find that firms with one standard deviation higher heat stress exposure have exhibited a consistent 45 basis points increase in un-levered expected annual returns on stocks. Gostlow (2021) finds evidence suggesting that hurricane risk commands a positive equity risk premium.[3] [4]

We apply our methodology to large life insurers and P&C insurers in the U.S. to understand their climate change risk exposure. We focus on life insurers' transition risk exposure and P&C insurers' physical risk, since life insurers have a much larger portfolio of financial assets ($9.4 trillion) than P&C insurers ($3 trillion), and P&C insurers are more naturally exposed to physical risk than life insurers.

In terms of life insurers' transition risk, we observe a notable increase in their transition climate beta during the 2019-2020 collapse of fossil fuel prices in the midst of substantial rise in the attention to climate risk as well as the number of climate-related regulations. Furthermore, our findings reveal a significant increase in the aggregate transition CRISK, which represents the expected capital shortfall in a severe transition risk scenario. Specifically, from 2019 to 2020, the aggregate CRISK of all life insurers in the U.S. increased by more than $150 billion, equivalent to approximately 28% of their market cap. This CRISK consists of two components, one of which is solely attributed to climate stress, the other

[3]In the fixed-income market, Auh et al. (2022) document that natural disasters have significant negative impacts on municipal bond prices for affected areas. In the real estate market, Ge et al. (2022) concludes flood risk has been priced in the real estate markets through flood insurance premiums, Ouazad (2022) employs deep out-of-the-money options to study investor beliefs on wildfire risk, highlighting the pricing of such risk in investor portfolios.

[4]There is a growing body of literature documenting that transition risk is priced in equity market (e.g., Engle et al., 2020; Choi et al., 2020; Alekseev et al., 2022; Zhang, 2023).

is existing capital shortfall due to high leverage. Our analysis reveals that the expected capital shortfall solely attributed to climate stress, known as *marginal CRISK* (mCRISK), experienced an increase of more than $85 billion during the same period. Compared to banks which experienced an increase of more than $500 billion in CRISK and around $100 billion in mCRISK over the same time period, the magnitude of transition climate beta is similar, while the CRISK and mCRISK in dollars are smaller, partly because insurers' balance sheets are smaller than banks'.

In terms of P&C insurers' physical risk, we find that large insurers' physical climate beta increased sharply during 2008-2010, likely due to the compounding impact of a higher leverage during the global financial crisis and severe damages from hurricanes in 2008, leading to a greater adverse effect than if the hurricanes had occurred without the financial crisis. In the cross-section, we find that small P&C insurers tend to have higher physical climate betas than large P&C insurers, and the climate betas of small insurers have been increasing. While the CRISKs of the top ten largest P&C insurers have mostly been negative, the CRISKs of smaller insurers (relative to their size) have been positive and increasing, suggesting that risks are concentrated on the smaller insurers.

We next empirically validate our climate beta estimates. To validate P&C insurers' physical risk beta, we first use municipal bond data to capture each state's exposure to physical climate risk. Specifically, we calculate each state's muni bonds' return sensitivity (beta) to our physical climate risk factor, i.e. state-level physical beta. Next, we use insurers' state-level premium data to measure their exposure to each state. Combining this data with states' muni bond betas, we obtain each insurer's weighted average of state-level physical beta, *Policy Portfolio Physical Climate Beta*. We find that this beta is significantly and positively correlated with insurers' market-based physical climate beta, offering empirical validation to our physical climate beta measure.

To validate life insurers' transition climate beta, we use detailed insurer asset holding data. We focus on life insurers' corporate bond holdings, which make up on average 34%

of their invested assets, their largest category of investment (Ge and Weisbach 2021). By linking corporate bonds to their respective industries using CUSIP and NAICS, we identify whether each bond is "brown", i.e. being exposed to transition risk.[5] We document that insurers that have a larger share of their corporate bond investments in industries facing greater transition climate risks have larger market-based transition beta. This correlation is significantly positive, offering validation to our measure of insurers' transition beta.

After validating our framework, we proceed to evaluate the exposure of both P&C insurers and life insurers to physical, transition, and market risks concurrently, quantifying their combined risk as *compound CRISK (CCRISK)*, following the methodology of Engle (2023). CCRISK represents the level at which, with a 1% probability, an insurer's capital shortfall would *not* exceed this value under compound stress. This methodology is valuable for assessing insurers' resilience when multiple risk dimensions materialize simultaneously. High tail dependence indicates that if one factor (e.g., physical risk factor) experiences an extreme decline, another factor (e.g., market factor) is more likely to experience an extreme decline at the same time. Therefore, ignoring tail dependence leads to an underestimation of risk. Our CCRISK metric adjusts for tail dependence among factors, ensuring policymakers do not underestimate potential co-movements of risks in extreme scenarios. Our analysis reveals that CCRISK levels for large P&C insurers have generally remained low or negative, while those for life insurers are moderate, less than $60 billion.

Contribution to Literature This paper contributes to the growing body of literature studying the effect of physical climate risk in various asset markets, including equities (Acharya et al., 2022; Alekseev et al., 2022), fixed-income (Acharya et al., 2022; Goldsmith-

[5] To ensure robustness, we use multiple approaches to identify brown corporate bonds. We classify corporate bonds as "brown" if they are issued by coal mining, gas mining, gas utilities, and electric utilities. Additionally, we characterize corporate bonds based on the issuer industry's stock return sensitivity to transition climate risk, measured by transition climate beta.

Pinkham et al., 2022; Painter, 2020; Auh et al., 2022; Liu et al., 2021), and real estate (Giglio et al., 2021b; Bernstein et al., 2019; Ge et al., 2022).[6] We propose a novel approach to measure forward-looking physical climate risk, which is new to the literature. Specifically, we develop a novel approach to construct a physical risk factor that is designed to decrease in value as physical risk escalates. Additionally, through event study analyses, we empirically demonstrate the decline of the proposed physical risk factor subsequent to natural disaster events with significant damages. Our factor can potentially be used to measure physical risks of firms beyond the insurance sector.

This paper is closely related to Jung et al. (2021), who propose a market-based approach called CRISK to measure climate transition risk exposure of financial institutions. We contribute beyond the existing CRISK framework in two important ways. First, we construct a physical risk factor and propose a way of measuring physical risk exposure, which can be generalized to other firms beyond the insurance section. Second, we focus on insurers, recognizing the critical importance of analyzing their liability side to comprehensively assess their climate risk exposure. Unlike banks, P&C insurers' liabilities predominantly stem from policyholder claims and obligations which can be directly exposed to physical climate risk.This distinction underscores the unique nature of insurers' risk profiles and necessitates a distinct approach to evaluating their climate risk.

Additionally, this paper contributes to the literature studying the impact of climate change on the insurance sector. We are the first paper, to our knowledge, to come up with measures of forward-looking physical risks faced by insurers. Previous studies (Hagendorff et al., 2015; Howerton and Bacon, 2017; Schuh and Jaeckle, 2023) have examined the relationship between disasters and insurers' stock prices. Some studies suggest that increased physical climate risk leads to an increase in demand for insurance. If insurers are able to adjust premia appropriately, physical climate risk might not impact expected profits (Holzheu et al., 2021; Alekseev et al., 2022; Grimaldi et al., 2020). However, other stud-

[6] Acharya et al. (2023); Giglio et al. (2021a); Hong et al. (2020); Krueger et al. (2020); Brunetti et al. (2022) provide comprehensive reviews of the literature on climate risk and financial system.

ies suggest that the above mechanism is limited due to financial and regulatory frictions. Ge (2022) document that following P&C divisions' losses due to unusual weather damages, life divisions change prices in order to generate more immediate financial resources. Ge and Weisbach (2021) suggest that when P&C insurers become more constrained due to operating losses (damage caused by weather shocks), they shift towards safer bonds on the asset side. Oh et al. (2022) find that insurers may be less prepared to deal with large losses and may respond by exiting markets or dropping important product features, though this kind of action is limited due to the rate-setting frictions. Massa and Zhang (2021) document that property and reinsurance companies react to Hurricane Katrina by shifting from bond financing to bank-based borrowing. While these papers suggest that insurers are implementing risk management strategies, it is not clear to what extent insurers could manage their risk of undercapitalization in the face of abrupt physical or transition risk realizations.

Outline of the Paper The remainder of the paper proceeds as follows: Section 2 describes the data. Section 3 develops various climate stress scenarios by constructing physical climate risk factors. Section 4 analyzes P&C insurers' exposure to physical climate risk, and section 5 studies life insurers' exposure to transition climate risk. Section 6 validates the measures, and section 7 analyzes compound risk. Section 8 concludes.

2 Data

Drawing from the insurance literature and recognizing that different types of insurers may face distinct climate risks, we classify insurers into two categories: P&C insurers and life insurers.[7] Our sample period covers 2000 to 2023.

[7] We identify P&C insurers using the NAICS (North American Industry Classification System) code 524126. Then we manually look up each firm's main focus and delete insurers who are not property (and casualty) insurance, multi-line insurance, specialty insurance, or reinsurance firms. We identify life insurers using SIC (Standard Industrial Classification) code 6311. Then we combine our data with Koijen and Yogo (2022) life insurer list to create our final list of life insurers.

Our analysis relies on three primary sources of data: (i) natural disaster event data to capture climate-related physical risk; (ii) stock and corporate bond data to construct market-based climate risk factors; and (iii) insurers' asset holdings and operational exposure data to investigate the relationship between climate risk and insurers' assets and liabilities.

Natural Disaster Event Data We utilize monthly data from National Oceanic and Atmospheric Administration (NOAA) National Center for Environmental Information to construct physical risk factors. This data is sourced from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) database, which provides information on natural hazard events and their economic losses across the country from 1980 to 2019. SHELDUS includes data on hurricanes, tornadoes, floods, wildfires, earthquakes, and more. Our focus is on assessing property damage resulting from coastal, drought, flooding, heatwaves, hurricanes, wind, wildfire, and winter weather disasters. In Figure 1, the map displays the average county-level property damage caused by all hazards from 2000 to 2019, with California, Texas, and Florida being particularly affected. Panel A of Figure 1 presents summary statistics of property damage for different hazard types, highlighting hurricanes and floods as the most destructive disasters.

To validate our physical risk factors, we employ the Billion-Dollar Weather and Climate Disasters Database maintained by NOAA, which tracks *daily* weather and climate events causing at least one billion dollars in damage from 1980 to 2023. This database provides additional details, including start and end dates, event summaries, CPI-adjusted estimated costs, and fatalities. It covers a range of disasters, such as droughts, floods, winter events, hurricanes, and wildfires. Panel B of Figure 1 presents the summary statistics of Billion Dollar disaster events, highlighting hurricanes, droughts, and wildfires as the most destructive shocks. While hurricanes, winter disasters, and winds typically last less than a week, flooding, wildfires, and droughts can persist for months.

Stock and Corporate Bond Data In the construction of physical risk factors, we use the U.S. P&C insurance companies' stock returns from CRSP-Compustat merged data set. Additionally, we gather corporate bond information from Mergent Fixed Income Securities Database (FISD), municipal bond characteristics from Mergent Municipal Bond Database, and municipal bond transaction data from MSRB's Municipal Securities Transaction Data.[8]

Insurers' Asset Holdings and Operational Exposure Data In order to measure insurers' liability-side exposures to physical risk, we utilize individual insurers' direct premiums earned (DPE) at the state-year level in homeowners' multiple peril line and commercial multiple peril line[9] from the National Association of Insurance Commissioners (NAIC) and SNL Financial.[10] To study the relationship between insurers' climate risk and their asset holding, we obtain insurers' holding data from Schedule D Part 1 of the Annual statement.

Municipal Bond Data In the validation of physical risk factors, we construct municipal bond returns using the Municipal Securities Rulemaking Board's (MSRB's) municipal bond transaction database, which includes information such as the CUSIP, trade date, the dollar price of the transaction, and type of transaction and the Mergent Municipal Bond Database, which contains issue amount, CUSIP, and issue ID.

[8]We thank authors of Acharya et al. (2022) for sharing their crosswalk to link municipal bond issuers with their corresponding county locations.

[9]We do not include less relevant business lines, including Auto, Product Liability, or Fire and Allied Lines Combined (which encompasses both wildfire and other fires resulting from electricity, faulty wiring or gas explosions.)

[10]The NAIC also offers insurers' direct losses incurred at the state-year level. Both DPE and LSS reflect insurers' liability exposure to each state and are strongly correlated. In this paper, we utilize DPE as a measure of insurers' exposure.

Sample Characterization

We focus on large insurance companies to understand their climate risk exposure Table 1 presents the summary statistics of the top ten P&C insurers and life insurers based on their average market capitalization from 2000 to 2021.[11]

P&C Insurers To understand P&C insurers' operational exposure to risky states, we construct *risky state exposure*, defined as the share of premium earned from risky states:

$$\text{Risky State Exposure}_{it} = \frac{\text{Premium Earned from Risky States}_{it}}{\text{Total Premium Earned}_{it}} \tag{1}$$

We identify risky states as Texas, Florida, and California, the top three states in terms of the average annual property damage caused by all hazards based on historical data from SHELDUS. These states have recorded average annual property damage caused by all hazards of $ 4.07 billion, $ 2.94 billion, and $ 2.36 billion, respectively, from 1980 to 2019 (all in adjusted U.S. dollars with the base year of 2019).

If an insurer's operation is well diversified across a number of states, even if it collects a large amount of premiums in a risky state, its diversification will dampen the effect of its total exposure to the risky states. To measure the degree of each insurer's operational portfolio diversification, we compute *Concentration* of each insurer's portfolio similar to the Herfindahl-Hirschman Index (HHI):

$$\text{Concentration}_{i,t} = \sum_{s \in S} \text{DPE Exposure}^2_{i,s,t} \tag{2}$$

where DPE $\text{Exposure}_{i,s,t}$ is insurer i's share of premium earned in state s in year t. A higher *Concentration* value indicates a lower level of diversification, implying that the insurer predominantly sells policies in a small number of states. *Concentration* equals 1 indicates that the insurer sold 100% of its policies in a single state.

[11]Note that we analyze American International Group separately given its specialty.

The last two columns in Panel A of Table 1 display P&C insurer operational exposure to states in the U.S. On average, the top ten P&C insurers collect approximately 18.6% of their premiums in risky states. However, there is significant variation among insurers, with percentages ranging from 3.6% to 29.2%. For example, Allstate earns approximately 16% of its premiums in California, and 7% each in Texas and Florida. The average *Concentration* of the top ten P&C insurers is 0.07, indicating that, an average insurer's operational exposure is well diversified across states.

Life Insurers To understand life insurers' corporate bond portfolio exposure to brown industries, we construct two measures. We define *brown share* as the fair value of brown corporate bonds divided by the fair value of all corporate bonds held by the insurer. To identify brown industries, we build on the general equilibrium model estimates of Jorgenson et al. (2018). We define brown industries as the top four industries: coal mining, gas mining, gas utilities, and electric utilities. We merge CUSIP-year-level holding data with Mergent and Compustat databases using 6-digit CUSIP to get the NAICS industry for each corporate bond.

Brown exposure is estimated based on a more general approach of Jung et al. (2023). Specifically, we compute the proportion of insurer i's corporate bond portfolio value that would be lost if policy P gets implemented.

$$\text{Brown Exposure}_{i,t}^{P} = \sum_{j \in J} w_{i,j,t} \, \text{Markdown}_{j}^{P} \tag{3}$$

where 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 policy P. We consider a policy with a carbon tax of $50 with a growth rate of 5%.[12] The key assumptions behind this approach are that (1) insurers lose the value of bonds proportionally to the drop in the

[12] Appendix Table A.5 reports the drop in industry output and we use the worst scenario (the last column) for the calculation of brown share and brown exposure.

output of the borrower's industry and (2) each insurer maintains its allocation of corporate bonds across industries as of time t.

The final two columns in Panel B of Table 1 present the two measures, brown share and brown exposure of the top ten P&C insurers. Based on the brown share measure, we find that 14.7% of their corporate bond portfolio is exposed to industries that are expected to be most adversely affected by carbon taxes. Based on the brown exposure measure, we find that, on average, they are expected to lose 4.6% of their corporate bond portfolio under a severe carbon tax scenario.[13] The brown exposure estimates are similar to that of large US banks, 3–4%, when computed in the same manner as in Jung et al. (2023).

3 Physical Climate Risk Factors

We construct various physical climate risk factors by forming portfolios that are designed to decrease in value as physical climate risk rises. In this section, we describe how we construct these factors, discuss their advantages over potential alternative methods, and empirically test their validity. We also briefly describe transition climate factors by Jung et al. (2021).

Our first proposed factor is constructed by using P&C insurers' stock returns. We focus on P&C insurers' operations because it is reasonable to hypothesize that P&C insurers are particularly affected by unexpected large natural disasters due to their role in providing property coverage against such events. While not all natural disasters are driven by climate change, the projected escalation of physical climate risk, including the increased occurrence of floods and wildfires, can cause an unexpected rise in claim payouts. Indeed, multiple insurance companies have stopped offering coverage in risky regions or exited the market.[14] Therefore, worse-than-expected natural disasters can cause substan-

[13] While not directly comparable, a study by New York Department of Financial Services (2021) reveals that in New York State, 11% of insurers' investments in equities and fixed income are allocated to carbon-intensive sectors.

[14] https://www.nytimes.com/2023/05/31/climate/climate-change-insurance-wildfires-california

tial losses for insurers, leading to a decline in their stock prices.

Conversely, if insurers can significantly raise premiums or if demand for insurance sharply increases, their stock returns can respond positively to disasters. However, while these conditions would make insurers more profitable as climate change risk rises, their significant concerns indicate that this is unlikely.

> “Losses and loss adjustment expenses are our largest liability, and severe weather (e.g., catastrophe events) can have a significant impact on those liabilities. Catastrophe events can potentially impact our pricing risks and the availability and cost of reinsurance. These events may be becoming more severe and less predictable as a result of climate change. [...] Changes in climate conditions may adversely impact the accuracy of the modeling tools that we use to estimate our exposures to catastrophe events." [Progressive Insurance Group, 2022]

> “In AM Best’s view, climate change represents the largest of these risks. With frequency and severity of weather-related events on the rise, insurers have been impacted severely by related losses, and pricing based on past experience remains challenging as catastrophe models have not yet fully considered the new normal." [AM Best, 2020]

To understand how P&C insurers are affected by disasters, we estimate their impact on P&C insurers’ losses, profitability, and rating with the following specification:

$$Y_{i,t} = \beta \text{ Disaster Exposure}_{i,t} + \text{Control}_{i,t} + \gamma_t + \delta_i + \epsilon_{i,t} \tag{4}$$

where the independent variable $Y_{i,t}$ is one of the four measures: $\mathbb{1}\{\text{Downgrade in rating}\}$, direct losses incurred, short-term profitability, and long-term profitability of P&C insurer i in year t. Disaster Losses$_{i,t}$ is the weighted average “riskiness" of states where the weight is the insurer’s operational exposure to the respective state. The “riskiness" of the state is proxied by the property damage based on SHELDUS (in logarithms):

$$\text{Disaster Losses}_{t,i} = \sum_{s\in S}\left[\left(\frac{DPE_{i,t,s}}{\sum_{s\in S} DPE_{i,t,s}}\right) \times \text{Property Damage}_{t,s}\right]$$

$\text{Control}_{i,t}$ includes reinsurance intensity, log assets, leverage, and RBC ratio. γ_t and δ_i capture the year and insurer fixed-effects. Table 2 suggests that following high disaster losses, P&C insurers are more likely to downgrade. Moreover, Table 3 indicates that P&C insurers' direct losses incurred increases and their short-term and long-term profitability decline with disaster losses.

Physical Climate Factors Motivated by the previous findings, we construct *insurer premium factor* by forming a portfolio of P&C insurer stock returns based on information on P&C insurers' operational exposure across states. Specifically, we merge P&C insurers' DPE with property damage from SHELDUS at the state-year level. Then, for each year, we compute each insurer i's physical risk exposure, denoted $RISK$, as:

$$RISK_{i,t} = \sum_{s\in S}\left[\left(\frac{DPE_{i,s,t-1}}{\sum_{s\in S} DPE_{i,s,t-1}}\right) \times \text{Property Damage}_{s,t-1}\right] \times \frac{1}{ME_{i,t-1}} \tag{5}$$

where $DPE_{i,s}$ denotes the direct premium earned by insurer i in state s, $\text{Property Damage}_{j,t-1}$ denotes the total property damage in state s in the previous year, and $ME_{i,t-1}$ denotes the market cap of insurer i in the previous year. The term $\frac{DPE_{i,s,t-1}}{\sum_{s\in S} DPE_{i,s,t-1}}$ proxies insurer i's premium exposure to state s and $Property\ Damage_{s,t-1}$ proxies the riskiness of state s. Some insurers also have operations other than P&C insurance. If P&C operations are less significant to the company, its stock returns will be less informative about insurers' physical risk exposure. To reflect this idea, we scale our measure by insurers' lagged market cap.

We explore alternative approaches to calculate the $RISK$ measure, such as using the standard deviation of past property damage as a proxy for the state's riskiness. Additionally, we consider subtracting direct premium earned from the product of $\frac{DPE_{i,s,t-1}}{\sum_{s \in S} DPE_{i,s,t-1}}$ and Property Damage$_{s,t-1}$ to measure the risk *relative* to the earned premium. (See Section B for the details.) We find that the constructed factors are highly related to each other, with correlations ranging between 0.90 and 0.94. In robustness analyses, we show that our main results remain robust when using the alternative approaches.

We form a portfolio of all US P&C insurers where the weight is $RISK$. Finally, we subtract the market return from the portfolio return to obtain the insurer premium factor. Intuitively, insurance companies with a substantial premium (policy) exposure to states characterized by high physical risk would be associated with elevated $RISK$. Consequently, the insurer premium factor gives greater weight to insurers with high $RISK$, while assigning lower weights to those with low $RISK$. We anticipate a decline in this factor after an unanticipated escalation in physical risk, such as a sharp increase in the frequency or severity of natural disasters.

The second physical climate factor, *insurer loss-to-equity factor*, is constructed based on P&C insurers' ratios of losses incurred relative to its market capitalization. Specifically, we compute the ratio by:

$$\text{Loss-to-Equity}_{i,t} = \frac{\sum_{s \in S} \bar{\rho}_{i,s,t-1} DPE_{i,s,t-1}}{ME_{i,t-1}} \tag{6}$$

where $\rho_{i,s,t}$ can be considered "risk weights" of insurer i in state s and year t:

$$\rho_{i,s,t} = \frac{Loss_{i,s,t}}{DPE_{i,s,t}} \tag{7}$$

and $\bar{\rho}$ are exponentially smoothed risk weights.[15] In contrast to the first factor, the loss-to-equity factor uses insurer-state-specific incurred losses relative to earned premiums, instead of relying on SHELDUS property damage data.

[15] We use exponentially weighted average of past observations to assign more weights to the recent observations for better forecasting. We use the optimal bandwidth.

The form of loss-to-equity measure resembles the inverse of the risk-based capital (RBC) ratio. The RBC ratio is a measure of an insurer's capital adequacy constructed by dividing its total adjusted capital by its required capital:

$$RBC_{i,t} = \frac{\text{Equity}_{i,t}}{\text{Required Equity}_{i,t}} \tag{8}$$

A higher RBC ratio indicates that the insurer has a larger buffer of capital to absorb potential losses and meet its obligations to policyholders. Our proxy measure, loss-to-equity, resembles the inverse of RBC ratio, and therefore a higher value indicates a higher risk.

Similar to the first physical factor, we form a portfolio of all P&C insurers in the U.S. where the weight is Loss-to-Equity. The loss-to-equity factor is computed as the portfolio return minus the market return. Presumably, insurance companies that experience larger losses are associated with higher risk because being subject to large losses means that insurers operate in areas where the unexpected losses are large. For example, in areas prone to hurricanes, if insurers charge annual premiums equaling the expected losses in a year, when costly hurricanes actually happen, losses will be large. In other areas that are not subject to costly events, insurers are less likely to suffer large losses. Therefore, by assigning greater weights to insurers with a higher Loss-to-Equity ratio, we anticipate a decline in the loss-to-equity factor following an unanticipated escalation in physical risks.[16]

Figure 2 shows the 6-month cumulative returns of the market portfolio (SPY), transition risk factor (stranded asset factor), and physical risk factor (insurer premium factor and insurer loss-to-equity factor). We observe high correlations among the constructed physical factors (Table A.2), as well as strong correlations between insurers' risk exposure on these factors (Table A.3). Hence, we primarily utilize the insurer premium factor as the physical climate factor in the following sections.

[16]We document supporting evidence in Figure A.1 showing that P&C insurers with high operational exposure to physical risk experienced higher incurred losses.

Unlike conventional climate shocks measured by temperatures or certain specific types of natural disasters, our approach offers distinct advantages. First, they are market-based, allowing us to incorporate the expectations of investors and reduce the reliance on uncertain geophysical climate models. Second, they assess the impact of physical climate risks on national financial markets as a whole, rather than being limited to specific regions. Focusing on specific disasters or geographical areas may not fully capture the systemic implications of climate risk. Finally, our market-based approach provides higher-frequency data compared to approaches that rely on sparse event series. Climate events such as extreme temperatures or natural disasters occur relatively infrequently, making it challenging to capture their effects accurately using event-based data alone.

Physical Climate Factor Responses around Natural Disasters To test whether the insurer premium factor captures physical climate risk, we conduct event study analyses using natural disaster events that caused more than \$1 billion in damages. We use the following specification to test the physical risk factor's responses to the disaster events:

$$PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n \, shock_{t-n} + MKT_t + \varepsilon_t \tag{9}$$

where PCF denotes the insurer premium factor, $shock_t$ 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. To control for overall market movements, we utilize the SPDR S&P 500 ETF as the market return, denoted as MKT. The coefficient γ is expected to be negative since the occurrence of a natural disaster should be bad news for insurers with larger weights in our factor, i.e., those with larger exposure to high-risk states relative to their market capitalization. The standard errors are adjusted using the Newey-West method to account for serial correlation.

Panel A of Figure 3 shows the cumulative γ coefficient along with a 95% confidence interval and suggests a negative response to the occurrence of natural disasters, consistent with the hypothesis.[17] Interestingly, the insurer premium factor takes more than 5 days to respond. We find supporting evidence that the slow response is associated with the fact that the impact (e.g., severity and duration) of the event is not obvious within the first few days of the event. In the case of one of the most damaging disasters, hurricane Katrina, on the first day of the event, August 26, 2005, an NYT article says "A Blast of Rain but *Little Damage* as Hurricane Hits South Florida."[18] On the fifth day, an article suggested the size of the damage.[19] Only after six days, on August 31, an article mentioned its impact on the financial market: "Markets Assess Hurricane Damage, and Shares Fall."[20] In Appendix Table A.4, we document the series of New York Times articles related to Hurricane Katrina.

In addition, we find that attention to natural disaster events typically peaks between 10 and 15 days after the first date of the disaster. To measure the attention to natural disaster events, we analyze the frequency of event mentions in New York Times (NYT) articles. We focus on the most significant hurricanes (in the 95th percentile of total losses) to capture their greater market impact and heightened public attention. Panel B of Figure 3 illustrates the pattern of these mentions following a hurricane event, with $t = 0$ indicating the event's start date. The figure reveals a consistent and relatively low number of mentions in the first five days, gradually increasing thereafter. The peak is observed on the 14th day, followed by a gradual decline in the number of mentions.

We conduct a series of robustness tests to ensure the reliability of the event study results. First, we find that the factors constructed using the alternative approaches to computing $RISK$, such as taking the standard deviation of property damage or subtracting the earned premium, exhibit similar responses to natural disaster events (Appendix Fig-

[17] Appendix Figure A.4 shows event study findings using the alternative physical risk factors (Insurer Loss-to-Equity Factor, Loss Deviation Factor, and Net Damage Factor). All physical climate factors exhibit similar responses.

[18] New York Times article, "A Blast of Rain but Little Damage as Hurricane Hits South Florida" mentions that "but there were *no reports of heavy damage* as the hurricane made landfall between North Miami Beach and Hallandale Beach shortly before 7 p.m."

[19] New York Times article, "Insurers Estimate Damage at $9 Billion"

[20] New York Times article, "Markets Assess Hurricane Damage, and Shares Fall"

ure A.4). Second, consistent results are obtained when flood events are excluded from the analysis to address the concern that the results are driven by floods that are predominantly covered by the National Flood Insurance Program (NFIP) rather than private insurers (Appendix Figure A.5). Third, we find that the results remain consistent when we consider the size of the disaster by defining $shock$ on the start day of the event as the log of damages, rather than the binary variable indicating the occurrence of the disaster (Appendix Figure A.6).

Transition Climate Factor Following Jung et al. (2021), we use the stranded asset factor as a proxy of transition risk. This factor is derived from the stranded asset portfolio developed by Litterman et al. (2021) and the World Wildlife Fund. The composition of the factor includes a 70% long position in VanEck Vectors Coal ETF (KOL), a 30% long position in Energy Select Sector SPDR ETF (XLE), and a short position in SPDR S&P 500 ETF Trust (SPY). The rationale behind this factor is that, during the transition towards a low-carbon economy, assets in the fossil fuel industries face the risk of devaluation and stranding. Consequently, the return on a stranded asset portfolio serves as a proxy measure that reflects market expectations regarding future climate transition risk. Jung et al. (2021) document that this factor tends to fall following climate policy-related events.

The physical and transition climate factor summary statistics (Table A.1) and correlation tables (Table A.2, Table A.3) are included in the appendix.

4 Insurers' Physical Risk Exposure

4.1 Physical Climate Beta

Following the standard factor model approach, we specify the model for insurer i's stock return as follows:

$$r_{i,t} = \beta_{i,t}^{Mkt} MKT_t + \beta_{i,t}^{Physical} PCF_t + \varepsilon_{i,t} \tag{10}$$

where $r_{i,t}$ is the stock return on insurer i, MKT_t is the market return measured as the return of S&P 500 ETF, and PCF_t denotes the insurer premium factor. Including the market factor in the model helps to control for confounding factors, such as the COVID shock and aggregate demand shock, that may influence both insurer stock returns and the physical risk factor. $\beta_{i,t}^{Mkt}$ and $\beta_{i,t}^{Physical}$ measure the sensitivity of insure i to overall market risk and physical risk. We call $\beta_{i,t}^{Physical}$ physical climate beta.

Panel A of Figure 6 presents the climate beta of the top ten largest insurers in the U.S. Not surprisingly, P&C insurers' climate betas are all positive, ranging between 0 and 1.2. We observe that all insurers exhibit similar movements in response to climate risk. Regarding the impact of natural disasters, we find that the physical climate betas for small insurers increase when they are affected by such events. Notable examples include Hurricane Katrina in 2005 and Hurricane Ike in 2008. These disasters likely intensified insurers' exposure to physical climate risk, leading to higher sensitivity during those periods. Among the top ten insurers, Hartford Financial Services (Ticker: HIG) stands out with the highest climate beta. This could be attributed to its significant exposure to risky states and a relatively lower market capitalization compared to other insurers. On the other hand, Progressive Corporation (Ticker: PGR), with a low DPE exposure, exhibits a relatively lower climate beta. In the next section, we formally test this relationship between physical climate beta and the insurers' premium (policy) exposure across states. As a robustness test, we include two additional factors, the interest rate factor, and credit risk factor, and we find that the results remain quantitatively similar (Figure A.3).

4.2 Physical CRISK and Marginal CRISK

Following the CRISK methodology in Jung et al. (2021), we compute the expected capital shortfall conditional on physical climate stress. We consider a scenario in which the physical climate factor falls substantially, corresponding to a 1% quantile of the return distribution, over six months. The CRISK is defined as the expected capital shortfall conditional on climate stress:

$$
\begin{aligned}
CRISK_{it} &= E_t[\text{Capital Shortfall}_i \mid \text{Climate Stress}] && (11)\\
&= E_t\left[k(D_{it} + W_{it}) - W_{it} \mid \text{Climate Stress}\right] && (12)\\
&= kD_{it} - (1-k) \underbrace{(1 - LRMES_{it})}_{=\exp\left(\beta_{it}^{Climate}\log(1-\theta)\right)} W_{it} && (13)
\end{aligned}
$$

where W_{it} is the market value of equity, D_{it} is the book value of debt, k is the prudential ratio of equity to assets, and θ is the climate stress level. We set the prudential capital fraction k to 8%, motivated by typical capital requirements for financial institutions (e.g., capital adequacy ratio). Therefore, the capital shortfall term in equation (11) can be interpreted as the difference between the prudential level of equity, 8% of quasi assets (the sum of D and W), and the equity that the financial institution holds, W.

To compute the conditional expected value of capital shortfall, we model long-run marginal expected shortfall (LRMES) based on climate beta and climate stress level, θ, as shown in equation (12). Climate beta is estimated from equation (10) and it captures the financial institution's stock return sensitivity to the climate factor (after controlling for the market factor). Climate stress is characterized by θ, and we calibrate θ to 20% for physical risk, as 20% decline corresponds to the 1% quantile of the six-month return distribution. CRISK is higher for insurers that are larger, more leveraged, and with higher climate beta.

Panel A of Figure 16 shows the estimated physical CRISK of the top ten largest U.S. P&C insurers. Notably, the magnitude of insurer physical CRISK (-50 to 20) is much lower than bank transition CRISK in Jung et al. (2021) ranging up to \$ 100 billion. This is partly due to the fact that these insurers are much smaller than large banks. If we compute the magnitude as relative to their market cap, the magnitude of P&C insurers' physical CRISK (-100% to 104% of their market cap) is also lower than banks' transition CRISK (-81% to 187% of their market cap).[21]

Because CRISK is a function of size, leverage, and beta, we introduce a related measure called marginal CRISK (mCRISK) to isolate and focus on the effect of climate beta. mCRISK captures the effect of climate stress in isolation from the realized undercapitalization as well as the effect of market stress. It is defined as the difference between CRISK and non-stressed CRISK:

$$mCRISK_{it} = (1-k)W_{it}LRMES_{it} \tag{14}$$

where $LRMES$ is the long-run marginal expected shortfall, defined as the expected firm equity multi-period arithmetic return conditional on a systemic climate change event:

$$LRMES_{it} = -E_t\left[R^i_{t,t+h}|R^{ClimateFactor}_{t+1,t+h} < C^{'}\right] \tag{15}$$

Panel A of Figure 12 plots the marginal CRISKs of the top ten large U.S. P&C insurers. Marginal CRISK isolates the effect of climate stress from the concurrent undercapitalization coming from the leverage effect. They range between \$ 0 and \$ 4 billion, suggesting no sign of substantial undercapitalization conditional on severe physical climate stress.

4.3 Physical CRISK Decomposition

To better understand what drives the decrease in physical CRISK in 2020, we decompose changes in CRISK into three components based on Equation 16:

[21] We compute the share of CRISK or mCRISK in terms of market cap by calculating the CRISK/market cap for each individual financial institution first, and then take the average across the top 10 institutions.

$$dCRISK = \underbrace{k \cdot \Delta DEBT}_{dDEBT} \underbrace{- (1-k)(1-LRMES) \cdot \Delta EQUITY}_{dEQUITY} + \underbrace{(1-k) \cdot EQUITY \cdot \Delta LRMES}_{dRISK} \tag{16}$$

The first component, $dDEBT = k \cdot \Delta DEBT$, is the contribution of the firm's debt to CRISK. CRISK increases as the firm takes on more debt. The second component, $dEQUITY = -(1-k)(1-LRMES) \cdot \Delta EQUITY$, is the effect of the firm's equity on CRISK. Here, $LRMES$ represents the average value of $LRMES_t$ and $LRMES_{t+1}$. CRISK increases as the firm's market capitalization deteriorates. The third component, $dRISK = (1-k) \cdot EQUITY \cdot \Delta LRMES$, is the contribution of an increase in climate beta to CRISK. Here, $EQUITY$ represents the average value of $EQUITY_t$ and $EQUITY_{t+1}$.

Panel A of Table 4 decomposes the change in CRISK of the top 10 P&C insurers in the U.S. during the year 2020 into three components. On average across the P&C insurers, the risk component (due to the rise in climate beta) contributed most, 97%, of the rise in CRISK during 2020.

5 Insurers' Transition Risk Exposure

5.1 Transition Climate Beta

Similarly, we estimate the transition climate beta for life insurers using the following model:

$$r_{i,t} = \beta_{i,t}^{Mkt} MKT_t + \beta_{i,t}^{Transition} TCF_t + \varepsilon_{i,t} \tag{17}$$

where $r_{i,t}$ is the stock return on life insurer i and TCF_t is the stranded asset factor. Panel B of Figure 6 exhibits the transition climate beta of large U.S. life insurers. All insurers' transition betas move similarly over time. Insurers' climate betas, like bankss, slightly decreased during the Global Financial Crisis (GFC) and dramatically increased during

2019-2020 when fossil fuel prices collapsed. The magnitude of the increase in insurers' climate beta during 2019-2020 is similar to banks in Jung et al. (2021).

5.2 Transition CRISK and marginal CRISK

Panel B of Figure 16 shows the transition CRISK of the large U.S. life insurers. In contrast to banks in Jung et al. (2021), insurers' CRISKs were stable during the GFC and 2019-2020 when fossil fuel energy prices collapsed.

Panel B of Figure 12 displays the transition marginal CRISK of life insurers in the U.S. The marginal CRISK of insurers and banks are similar, close to zero for most of the time, and went up during 2019-2020, reaching more than \$10 billion in 2020. The range of insurer marginal CRISK scaled by market capitalization ranges between -66% to +31%, and this is comparable to those of banks (-41% to +33%). Due to the size effect, banks' marginal CRISK can reach \$ 120 billion while the maximum of insurers is less than \$ 15 billion.

5.3 Transition CRISK Decomposition

To gain insights into the factors contributing to the increase in transition CRISK in 2020, we decompose CRISK into three components according to Equation 16. Panel B of Table 4 shows the contribution of three components. On average, the risk (i.e., increase in climate beta) contributed 59% and the equity deterioration contributed 29% to the change in CRISK during 2020.

6 Validation

6.1 Insurers' Physical Climate Beta and their Liability Exposure

In this section, we validate our methodology by comparing P&C insurers' physical climate beta, estimated from equation (10), with their *policy portfolio climate beta*, reflecting their portfolio of insurance policies.

To conduct this test, we first measure the physical climate risk of each county by employing municipal bond returns, as previous studies (e.g. Auh et al., 2022) show that physical climate risk is priced in the municipal bond market. To account for the infrequent trading of municipal bonds, we focus on counties with a sufficient number of bond transactions (at least 10 times per quarter), which results in a sample of 295 counties. Then, we compute the average of all municipal bond monthly returns within the same county weighted by issue amount and trading interval, following the approach of Auh et al. (2022). Once county-level monthly returns on municipal bonds are obtained, we estimate the physical climate beta for each county using Equation 10 on a monthly frequency.

To aggregate county-level physical climate beta to state-level physical climate beta, we focus on the positive climate betas and counties with high climate risk exposure to capture the asymmetric payoff to insurers. Insurers are more likely to experience losses from unexpected claims related to severe weather events in risky counties (associated with positive climate betas), while they do not have a corresponding advantage or significant gains from policies in areas with negative climate betas.[22] Therefore, we retain counties with positive climate beta and measure a state's climate beta as the 99th percentile of the climate beta of municipal bonds across all counties within the state.

After obtaining the state-level physical climate beta estimates, we construct a panel of policy portfolio climate beta by computing the weighted average climate beta for each insurer, where the weight is the DPE exposure of an insurer i to the corresponding state s:

[22] It is possible for insurers to charge higher than actuarially fair premiums in counties with negative climate betas (to subsidize other counties). However, we assume this effect is not first-order.

$$\text{Policy Portfolio Physical Climate Beta}_{i,t} = \sum_{s \in S} w_{i,s,t} \, \beta_{s,t}^{Physical} \tag{18}$$

where the weight $w_{i,s,t}$ is the DPE share of insurer i's premiums from state s in year t. $\beta_j^{Physical}$ denotes the physical climate beta of state s.

Figure 13 is a binned scatter plot of market-based physical climate beta against the policy portfolio climate beta. The figure suggests that the two are positively correlated. We formally test this with the following OLS specification:

$$\beta_{it}^{Physical} = a + b \text{ Policy Portfolio Physical Climate Beta}_{it} + \text{Insurer Controls} + \delta_i + \varepsilon_{it} \tag{19}$$

The dependent variable, $\beta_{it}^{Physical}$ is insurer i's time-averaged daily climate transition beta for each year. Table 5 shows the result. Column (2) includes insurer control variables, size and leverage. Size is the log of total assets. Leverage is defined as 1 plus its book value of liabilities divided by its market value of equity. Column (3) adds insurer fixed effects to control for unobservable time-invariant insurer characteristics. Standard errors are clustered at the insurer level. We find that b is positive and significant in all specifications.

6.2 Insurers' Transition Climate Beta and Their Asset Holdings

In this section, we test whether insurers' exposure to transition risk, proxied by transition climate beta, aligns with insurers' asset holdings. To test this, we focus on life insurers' bond holdings because their equity holdings tend to be small, which can be partly explained by the high capital requirements on equities (Koijen and Yogo, 2023). First, we construct a panel of bond portfolio climate beta by computing the weighted average climate beta for each insurer where the weight is the proportion of bond holding in the respective industry and each investment is assigned the climate beta of the respective industry:

$$\text{Bond Portfolio Transition Climate Beta}_i = \sum_{j \in J} w_j \ \beta_j^{Transition} \tag{20}$$

where the weight, w_j is the proportion of investment made to the respective industry j. $\beta_j^{Transition}$ denotes the transition climate beta of industry j, and it is computed as the value-weighted average climate beta of firms in each 3-digit NAICS industry. The industry climate betas are computed based on all listed firms in the U.S. following Jung et al. (2021). Figure 14 is a binned scatter plot of the market-based transition climate beta against the bond portfolio climate beta. The figure suggests that these two are positively correlated We formally test this with the following OLS specification:

$$\beta_{it}^{Transition} = a + b \text{ Bond Portfolio Transition Climate Beta}_{it} + \text{Insurer Controls} + \delta_i + \varepsilon_{it} \tag{21}$$

The dependent variable, $\beta_{it}^{Transition}$ is insurer i's time-averaged daily climate transition beta for each year. Insurer control variables include size and leverage, defined the same as in the previous subsection. Table 5 shows the result. Column (2) includes insurer control variables. Column (3) adds insurer fixed effects to control for unobservable time-invariant insurer characteristics. Standard errors are clustered at the insurer level. We find that b is positive and significant across all specifications, suggesting that insurers' exposure to transition risk is in line with their asset holdings.

7 Compound CRISK Incorporating Tail Dependence

The previous analyses have focused on either transition risk or physical risk individually. In this section, we expand our analysis to encompass market, physical, and transition risks concurrently, considering both P&C and life insurers. Building upon the methodology of Engle (2023), we propose a compound CRISK (CCRISK) measure that incorporates tail dependence.

7.1 Tail Dependence

An important element in extending the analyses to incorporate multiple stresses simultaneously is tail dependence, which measures the likelihood of two stresses occurring conditional on the realization of either one. Understanding tail dependence is crucial in accurately assessing and managing risks, especially when multiple stresses interact non-linearly. For instance, during financial market stress like the financial crisis, natural disasters may amplify stress levels in the insurance sector beyond the combined impact of each event happening independently. It is worth noting that tail dependence is not captured by the correlation, which measures linear relationships.

Figure 15 plots the empirical tail dependence structure of the three factors. The x-axis represents the probability of one stress occurring, and y-axis represents the probability of both (three) stress events realizing conditional on the realization of a single stress in panels a, b, and c (panel d). The sample is based on the daily 6-month return series for 2000-2021.

Interestingly, the physical factor and the market factor show some tail dependence in panel (c). For example, as the market stress (or physical stress) gets more extreme (x-value approaches zero), the probability of both stresses realizing conditional on the single stress (y-value) is 13%. Considering this tail dependence, the previous 1-percentile stress quantile is adjusted to 0.35-percentile stress for *each* factor.[23] This corresponds to 39%, 62%, and 25% decline in market factor, transition factor, and physical factor, respectively.

7.2 Compound CRISK (CCRISK)

With the estimated tail dependence estimates and three betas, we can compute CCRISK. The three betas are estimated from:

$$r_{it} = \beta_{it}^{Mkt} MKT_t + \beta_{it}^{Trans} TCF_t + \beta_{it}^{Phys} PCF_t + \varepsilon_{it} \tag{22}$$

[23]See Appendix D for a detailed description of the estimation methodology.

The compound CRISK (CCRISK) can be computed as:

$$CCRISK_{it} = kD_{it} - (1-k) \cdot W_{it} \cdot (1 - LRMES_{it})$$
$$LRMES_{it} = 1 - \exp\left(\beta_{it}^{Mkt} \log(1-\theta^{Mkt}) + \beta_{it}^{Trans} \log(1-\theta^{Trans}) + \beta_{it}^{Phys} \log(1-\theta^{Phys})\right)$$

where the stress levels are determined from the tail dependence estimates from the previous subsection (i.e., $\theta^{Mkt} = 0.39, \theta^{Trans} = 0.62, \theta^{Phys} = 0.25$).

Figure 16(a) shows the estimated CCRISK for the top 10 P&C insurers and Figure 16(b) shows that for the top 10 life insurers. Even after considering all three dimensions of risk, we observe that the top 10 P&C insurers maintain negative CCRISK values in the recent period, consistent with our earlier findings focusing solely on their physical risk exposure. This suggests that the physical risk is more relevant for P&C insurers than the transition risk. Furthermore, we find that CCRISK levels for P&C insurers have generally remained low or negative, while those for life insurers are moderate, less than $60 billion.

These results stem from the fact that P&C insurers have higher physical climate betas compared to life insurers, while life insurers have higher transition climate betas compared to P&C insurers. To show this, we regress the climate betas on insurer type and characteristics:

$$\text{Climate Beta}_{i,t} = b\ \mathbb{1}(\text{is P\&C})_i + \text{Insurer Characteristics}_{i,t} + \gamma_t + \epsilon_{i,t} \tag{23}$$

where Climate $\text{Beta}_{i,t}$ represents either $\beta_{i,t}^{Phys}$ or $\beta_{i,t}^{Trans}$ estimated from equation (22). $\mathbb{1}(\text{is P\&C})_i$ is an indicator variable that takes a value of one if it is a P&C insurer, to zero if it is a life insurer. γ_t controls for the time-fixed effect. Table 6 shows that the coefficients on the dummy variable are positive for physical climate beta and negative for transition climate beta under all specifications. This suggests that P&C insurers are relatively more exposed to physical climate risk, while life insurers are more exposed to transition climate risk, conditional on the observables. Additionally, the negative coefficients on the size imply that larger insurers tend to have lower exposures, whereas the positive coefficients on leverage indicate that insurers with higher leverage are more exposed.

8 Conclusion

This paper evaluates P&C insurers' physical climate risk exposure and life insurers' transition risk exposure. First, we develop physical risk factors based on P&C insurers' stocks based on each insurer's operational exposure to each state in the U.S., taking into account states' different physical climate risk exposure. We then estimate the dynamic climate beta, which captures the stock return sensitivity of each insurer to the physical risk factor. Second, we follow Jung et al. (2021) to measure life insurers' exposure to transition climate risk. By computing the expected capital shortfall of insurers under various climate stress scenarios, we further quantify the potential financial implications of climate risk to the insurance sector.

In terms of physical risk for P&C insurers, we find that the top ten P&C insurers mostly had negative CRISK values (excess reserves), indicating no sign of potential systemic undercapitalization under physical climate stress. In terms of transition risk for life insurers, we observe a notable increase in their transition climate beta during the 2019-2020 fossil fuel price collapse. The aggregate transition CRISK for life insurers in the U.S. also significantly rose by more than $ 150 billion, equivalent to around 28% of their market cap. Excluding concurrent undercapitalization, the marginal CRISK attributed solely to climate stress increased by more than $ 85 billion during the same period.

On the physical climate risk side, We validate our method by examining insurers' policy exposure in each state and the corresponding state-level physical risk. Our findings indicate that the market-based physical climate beta reflects insurers' policy portfolio composition. Insurers with a greater proportion of policies in states facing higher physical climate risks exhibit higher exposure to physical climate risk, while those with a lower allocation in such states have lower exposure.

Empirical validation of the transition climate risk factor and climate beta estimates is conducted using granular data on insurers' asset holdings and the industry exposure in those holdings. We find that the market-based transition climate beta reflects insurers' bond portfolio composition. Insurers with a higher proportion of their corporate bond holdings in industries that are more affected by transition climate risks are more exposed to transition climate risk compared to those with a lower allocation in such industries.

In conclusion, this study enhances our understanding of the climate risk exposure of life and property and casualty insurers in the U.S. We find that transition risk can have a significant impact, while physical risk has a relatively lower impact on insurers' capital shortfall and risk sensitivities. Looking beyond this paper, fruitful directions for future research include exploring insurers' responses to physical and transition climate shocks, specifically focusing on their adjustments in policy pricing and quantity. This line of research will provide further insights into insurers' risk management strategies and their efforts to address the financial implications of climate change.

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Tables

TABLE 1: TOP 10 INSURER SUMMARY STATISTICS

Panel A: P&C Insurers Summary Statistics

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

Panel B: Life Insurers 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

Note: Panel A shows the summary statistics of P&C insurers. RSE (Risky State Exposure) represents the share of direct premiums earned in risky states (California, Florida, and Texas) for each insurer in each year during the sample period of 2000-2021. Panel B shows the summary statistics of life/health insurers. The Brown Share represents the ratio of the fair value of corporate bonds within brown industries to the total fair value of corporate bonds held by each insurer in each year during the same sample period. We identified brown industries as Coal Mining (NAICS Industry 2121), Gas Mining (NAICS Industry 211130), Gas utilities (NAICS Industry 2212), and Electric utilities (NAICS Industry 2211). According to Jorgenson et al. (2018), their estimated drop in industry output under a severe carbon tax scenario ($50 tax, 5% growth rate) are 33.8%, 15.7%, 15.4%, and 12.4%, respectively. *Brown Exposure* is the proportion of insurer i's corporate bond portfolio value that would be lost if a severe carbon tax policy ($50 growing at 5% annually) gets implemented. Specifically, it is calculated as: $Brown\ Exposure_{i,t} = \sum_{j \in J} w_{i,j,t}\ Markdown_j$ where w_{ijt} is the proportion of insurer i's corporate bond invested in industry j at time t, $Markdown_j$ is the drop in the output of industry j under the carbon tax. *Market cap*, *Asset*, and *Equity* are in log.

TABLE 2: P&C INSURERS' RATINGS AND WEATHER LOSSES

Ratings in Ordinal Numbers	P&C Insurers' Rating Downgrade (y) (Downgrade = 1)							
	OLS				Probit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster Loss (y-1)	0.002***	0.002**	0.002**	0.002***	0.018***	0.016***	0.018***	0.016***
	(2.68)	(2.53)	(2.57)	(2.66)	(3.61)	(3.19)	(3.61)	(3.21)
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
N	23782	13218	23781	13217	23782	23780	23782	13218

Notes: This table presents results on how P&C insurers' AM Best ratings are related to weather loss estimated in Equation 4. Weather loss for each P&C insurer is computed as the premium exposure-weighted average of state-level total property loss due to natural hazards according to SHELDUS (excluding floodings). Weather $\text{loss}_{t,i} = \sum_{s\in S}\left[\left(\frac{DPE_{i,t,s}}{\sum_{s\in S} DPE_{i,t,s}}\right) * \text{Property Damage}_{t,s}\right]$. The outcome variable P&C Insurers' Rating Downgrade (y) is 1 if the change of P&C Insurers' Rating from year $(y-1)$ to year y is negative. Controls are insurers' assets and leverage. Both ratings use the first rating that P&C insurers receive in the year. We match P&C insurers' unexpected weather loss from the end of year $(y-1)$ to the change of rating in year y. Controls, when included, contain P&C insurers' asset and leverage in year y. Columns (1) to (4) use OLS, and columns (5) to (8) probit. Standard errors are clustered at the individual insurer level. t-statistics or z-statistics are in parentheses. The sample period is from 1998 to 2020. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE 3: INSURERS' OPERATIONAL EXPOSURE TO PHYSICAL RISK VS. REALIZED LOSS

Panel A: Direct Losses Incurred					
	Direct Losses Incurred (y)				
	(1)	(2)	(3)	(4)	(5)
Disaster Loss (y)	0.228***	0.153***	0.095***	0.168***	0.104***
	(14.08)	(10.09)	(11.30)	(10.59)	(11.46)
Insurer Controls	No	Yes	Yes	Yes	Yes
Insurer FE	No	No	Yes	No	Yes
Time FE	No	No	No	Yes	Yes
N	21,809	21,809	21,728	21,809	21,728
Panel B: Short-term Profitability					
	Net Underwriting Gains (y) to Asset (y-1)				
	(1)	(2)	(3)	(4)	(5)
Disaster Loss (y)	-0.003***	-0.004***	-0.005***	-0.004***	-0.005***
	(-3.54)	(-3.58)	(-6.95)	(-3.49)	(-7.28)
Insurer Controls	No	Yes	Yes	Yes	Yes
Insurer FE	No	No	Yes	No	Yes
Time FE	No	No	No	Yes	Yes
N	20,765	20,765	20,704	20,765	20,704
Panel C: Long-term Profitability					
	Net Underwriting Gains (y) to Asset (y-1)				
	(1)	(2)	(3)	(4)	(5)
Disaster Loss (y-3)	-0.001**	-0.001**	-0.001***	-0.001	-0.001*
	(-2.01)	(-2.19)	(-2.58)	(-1.36)	(-1.65)
Insurer Controls	No	Yes	Yes	Yes	Yes
Insurer FE	No	No	Yes	No	Yes
Time FE	No	No	No	Yes	Yes
N	17,830	17,830	17,761	17,830	17,761

Notes: This table presents results on how P&C insurers' realized losses are related to physical risk estimated in Equation 4. P&C insurer-level operational exposure to physical risk is computed as the weighted average "riskiness" of states where the weight is the insurer's operational exposure to the respective state. The "riskiness" of state is proxied by the property damage based on SHELDUS (in logarithms). Realized losses are measured as the direct losses incurred (Panel A), short-term profitability (Panel B), and long-term profitability (Panel C). Profitability is computed as the net underwriting gains scaled by lagged asset of the previous year. The sample comprises all individual P&C insurers, and the data spans from 1997 to 2019. Standard errors are clustered at the individual insurer level. t-statistics are in parentheses. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE 4: CRISK DECOMPOSITION

Panel A: P&C Insurers CRISK

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			-6.05	1.37	-1.54	-5.88

Panel B: Life Insurers CRISK

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

Note: CRISK(t) is the insurer's physical or transition CRISK at the end of 2020, and CRISK(t-1) is CRISK at the end of year 2019. dCRISK = CRISK(t)-CRISK(t-1) is the change in CRISK during 2020. dDEBT is the contribution of the firm's debt to CRISK. dEQUITY is the contribution of the firm's equity on CRISK. dRISK is the contribution of increase in volatility or correlation to CRISK. All amounts are in billion dollars.

Table 5: Climate Beta Validation

Panel A: P&C Insurer Climate Beta and Policy Portfolio Climate Beta			
	Physical Climate Beta		
	(1)	(2)	(3)
Policy Portfolio Climate Beta	0.102^{***}	0.089^{***}	0.071^{***}
	(5.06)	(4.35)	(2.70)
Size		-0.046^{***}	-0.007
		(-5.70)	(-0.37)
Leverage		0.011^{***}	0.011^{***}
		(7.90)	(4.73)
Insurer Controls	No	Yes	Yes
Insurer FE	No	No	Yes
N	279	279	279

Panel B: Life Insurer Climate Beta and Bond Portfolio Climate Beta			
	Transition Climate Beta		
	(1)	(2)	(3)
Bond Portfolio Climate Beta	0.950^{***}	1.090^{***}	1.185^{***}
	(4.02)	(4.85)	(4.67)
Size		-0.012	0.044
		(-1.53)	(1.51)
Leverage		0.006^{***}	0.004^{**}
		(3.99)	(2.08)
Insurer Controls	No	Yes	Yes
Insurer FE	No	No	Yes
N	293	292	292

Notes: This table shows results from Equation 19 and Equation 21. t-statistics are in parentheses. The sample comprises all P&C insurers and life insurers in the U.S., and the annual data spans from 1997 to 2019. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

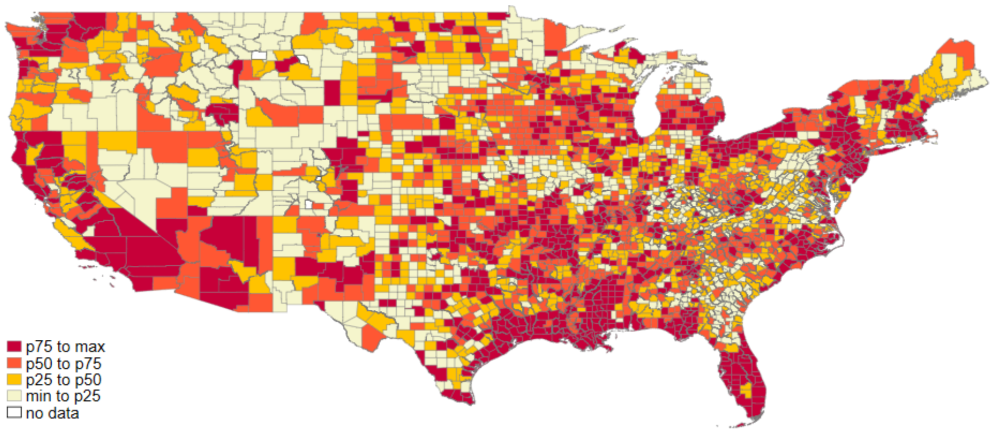
Table 6: Climate Betas and Insurers' Types

	Physical Climate Beta			Transition Climate Beta		
	(1)	(2)	(3)	(4)	(5)	(6)
1(is P&C)	0.076***	0.090***	0.082***	-0.061**	-0.039**	-0.050***
	(0.027)	(0.020)	(0.023)	(0.023)	(0.016)	(0.015)
Size		-0.036***	-0.029***		-0.028***	-0.038***
		(0.008)	(0.011)		(0.009)	(0.008)
Leverage		0.005***	0.003*		0.005***	0.005***
		(0.001)	(0.001)		(0.002)	(0.001)
Year-Quarter FE	No	No	Yes	No	No	Yes
R^2	3.13	14.1	52.0	2.66	15.5	45.6
Observations	2,317	2,317	2,317	2,317	2,317	2,317

Note: This table shows results from regression 23, using daily data from 2001 to 2022. Daily betas and controls are aggregated to the quarterly level by taking the average of daily data. All standard errors are clustered at the insurer level. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Figures

FIGURE 1: NATURAL DISASTER DATA DESCRIPTIVE STATISTICS



Panel A: SHELDUS Summary Statistics

Hazard	Average(Billions $)	Std	Median(Billions $)	Max(Billions $)
Hurricane	23,557	77,612	31	470,925
Flooding	9,456	51,986	714	565,212
Severe Storm	2,477	6,958	621	73,136
Winter	1,788	4,117	327	33,512
Wildfire	1,695	13,810	36	194,262
Drought	564	1,443	31	9,087
Coast	47	173	1	1,355
Heat	14	27	1	108

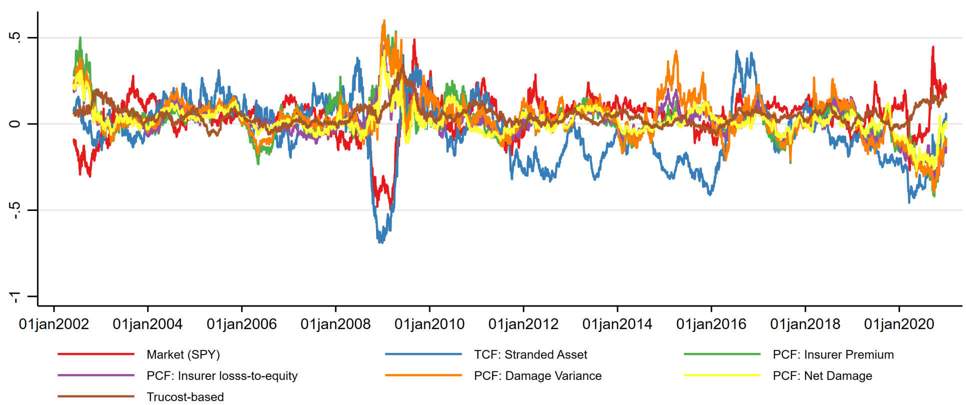
Panel B: Billion Dollar Summary Statistics

Harzard	Duration (Days)	Loss (Billions $)	Average Loss(Billions $)	Deaths
Hurricane	4	28,557	8,216	156
Drought	289	10,056	1,437	46
Wildfire	181	7,052	1,008	23
Winter	5	4,028	785	32
Flooding	21	3,729	780	13
Severe Storm	3	2,386	958	10

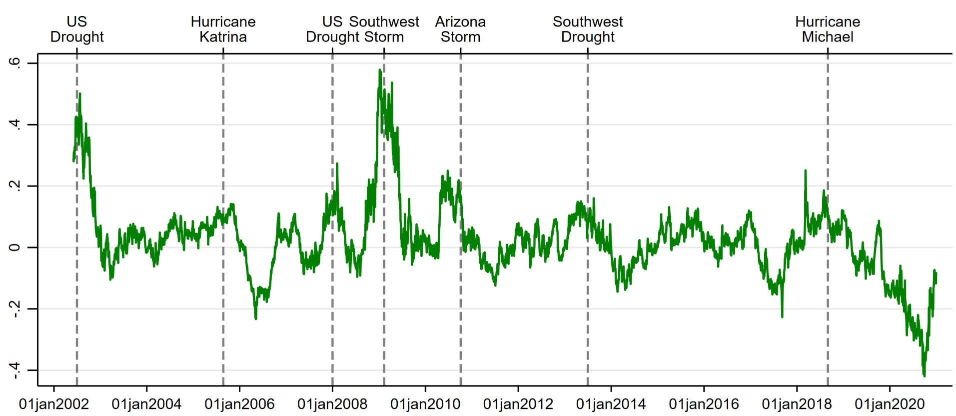
Note: The map shows the county distribution of SHELDUS average property damage. Panel A shows the summary statistics of SHELDUS country-level property damage data. Panel B shows the summary statistics of Billion Dollar Natural Disasters. Loss is the average total loss across events. The average loss is the average loss per day. We keep only the first 7 days for hazards that last for more than 7 days when calculating the average loss. The sample period of both the map and the table is 2000-2022.

FIGURE 2: 6-MONTH CUMULATIVE RETURNS

(A) MARKET, TRANSITION, AND PHYSICAL FACTORS



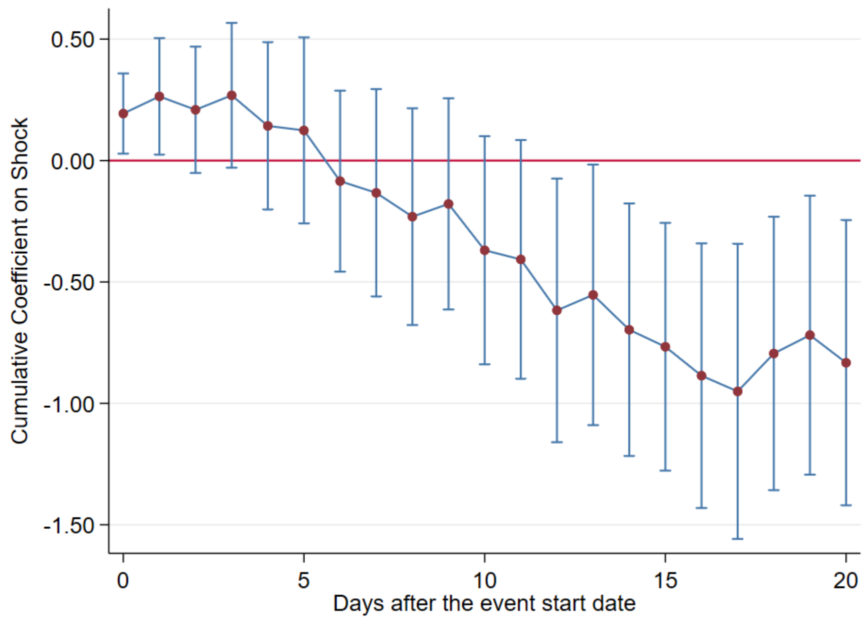
(B) INSURER PREMIUM FACTOR



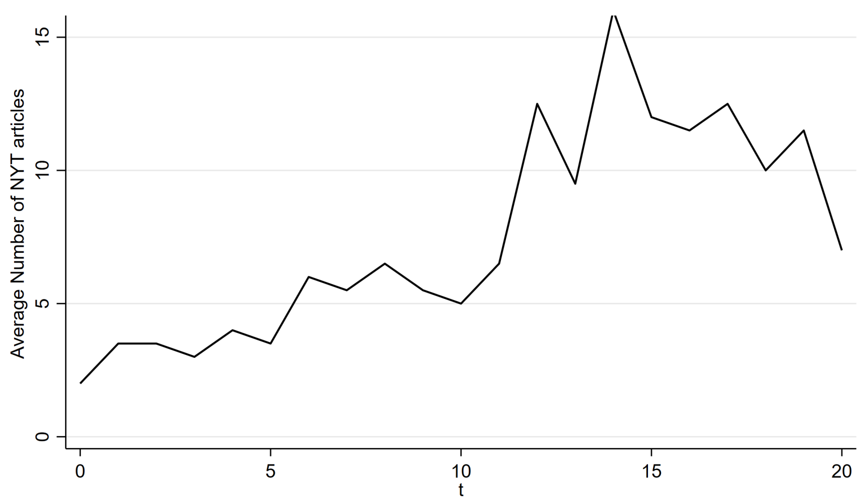
Note: Panel A shows the 6-month cumulative returns of the market portfolio (SPY), transition risk factor (stranded asset factor), and physical risk factors: insurer premium factor, insurer loss-to-equity factor, damage variance factor, net damage factor, and trucost-based factor. Panel B shows the 6-month cumulative returns of insurer premium factor, annotated with relevant climate events.

Figure 3: Responses around Natural Disaster Events

(a) Insurer Premium Factor Responses



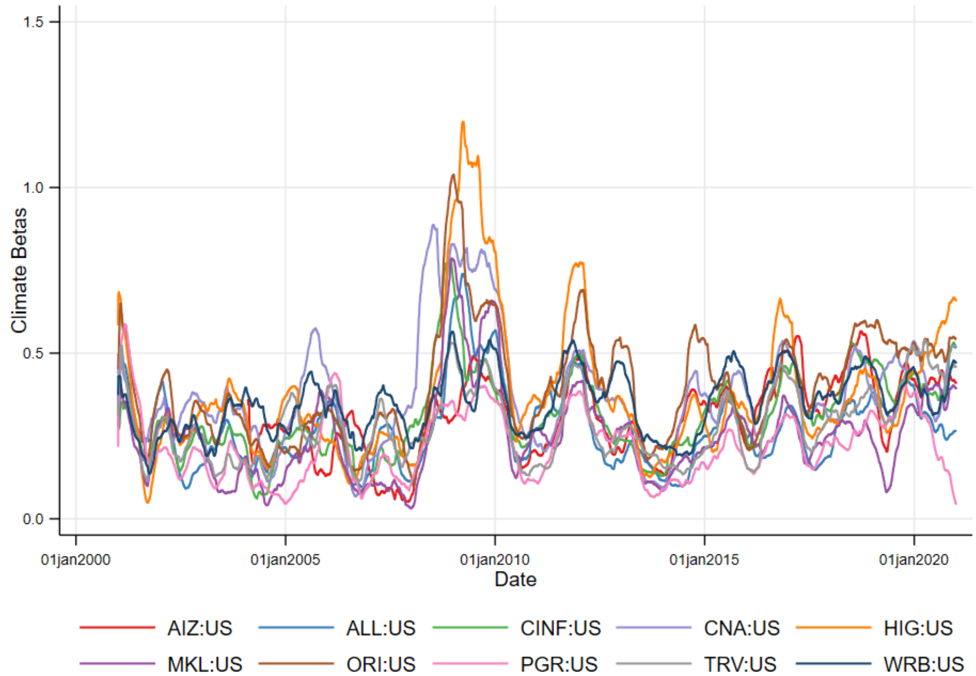
(b) NYT News Responses



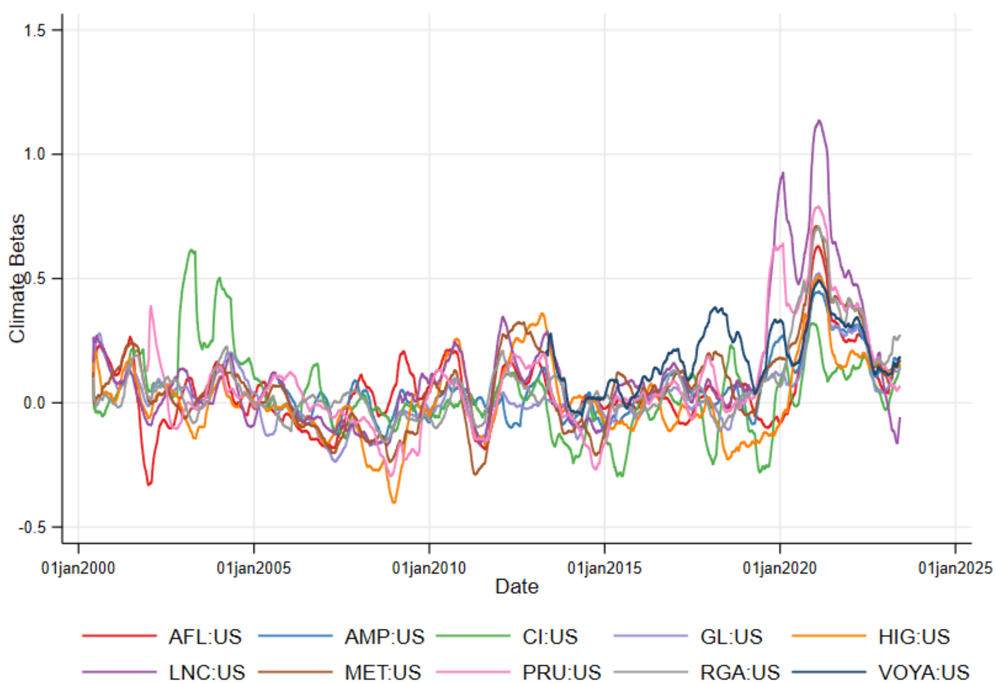
Note: Panel A shows the Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$. $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. In the sample period spanning from 2001 to 2020, a total of 149 natural disaster events were recorded. Each physical risk factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval. Panel B displays the frequency of mentions of "hurricane" in NYT articles following a hurricane. The start date of the event is represented as t=0. The average number of mentions is calculated across the most significant hurricanes (95th percentile of all hurricanes generated loss). We focus on these large hurricanes due to their heightened public attention and assumed greater impact on the market.

FIGURE 4: CLIMATE BETA

(A) PHYSICAL CLIMATE BETA OF P&C INSURERS IN THE U.S.



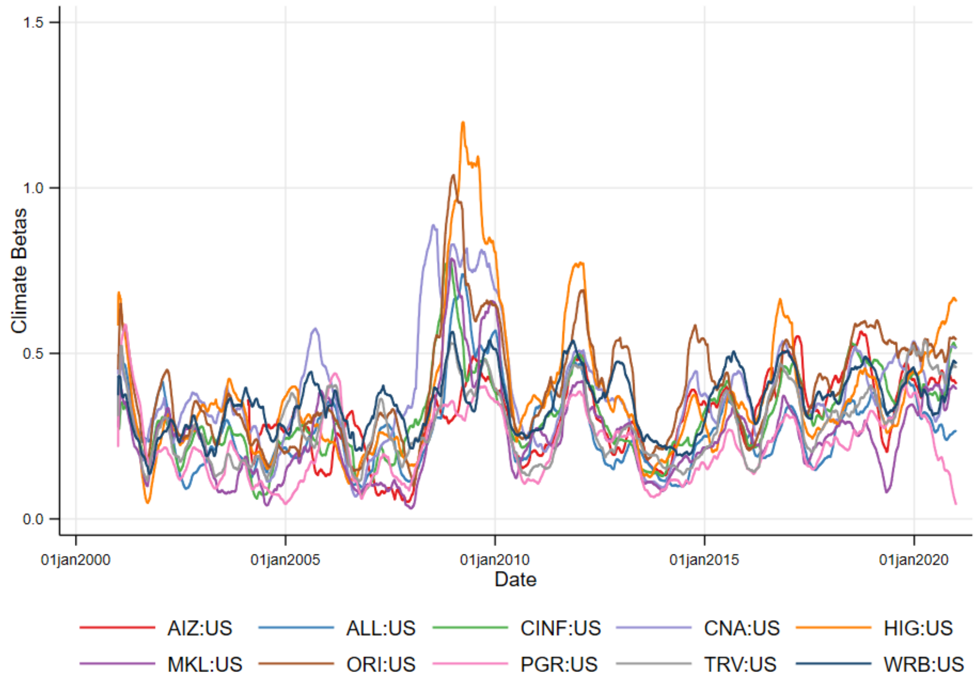
(B) TRANSITION CLIMATE BETA OF LIFE INSURERS IN THE U.S.



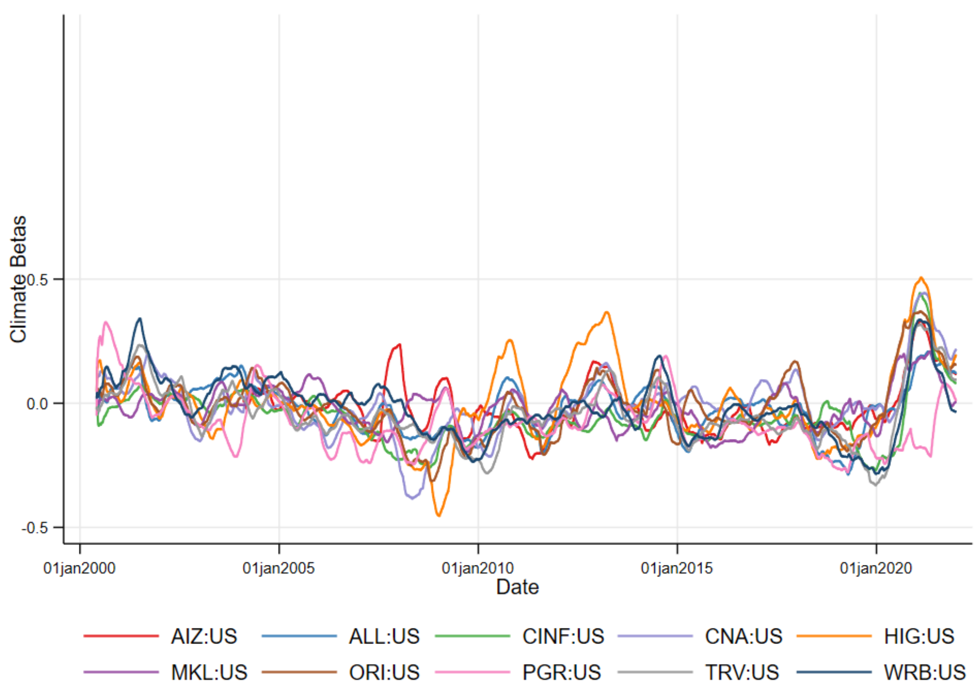
Note: Panel A displays the climate beta of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in the U.S. in Table 1. The sample period is from January 2002 to December 2020. Panel B exhibits the climate beta of life insurers in the U.S.. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

Figure 5: Climate Beta of P&C Insurers in the U.S.

(a) Physical Climate Beta



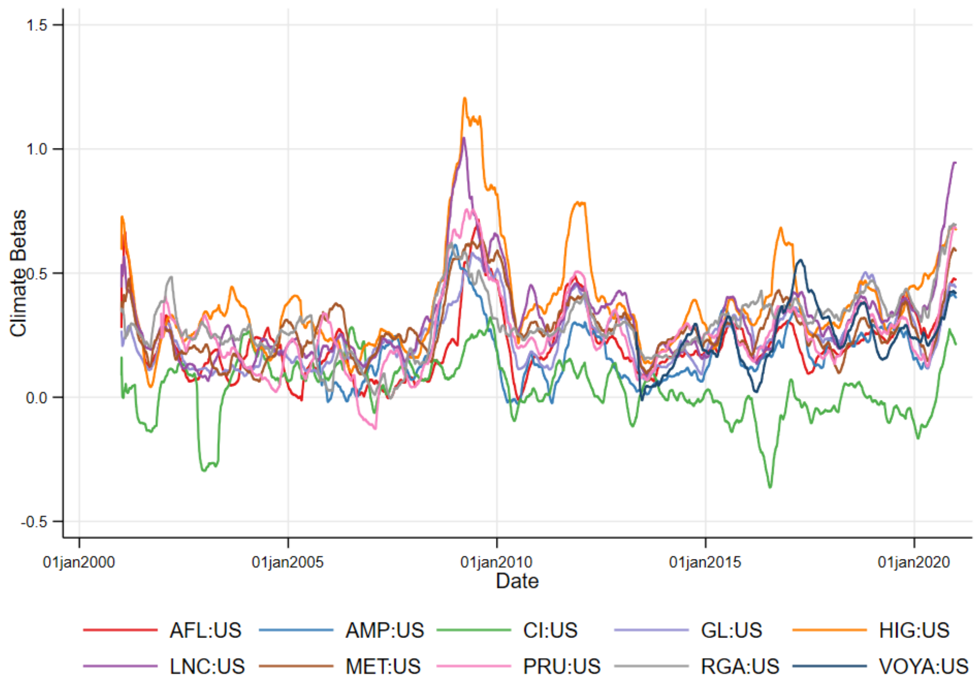
(b) Transition Climate Beta



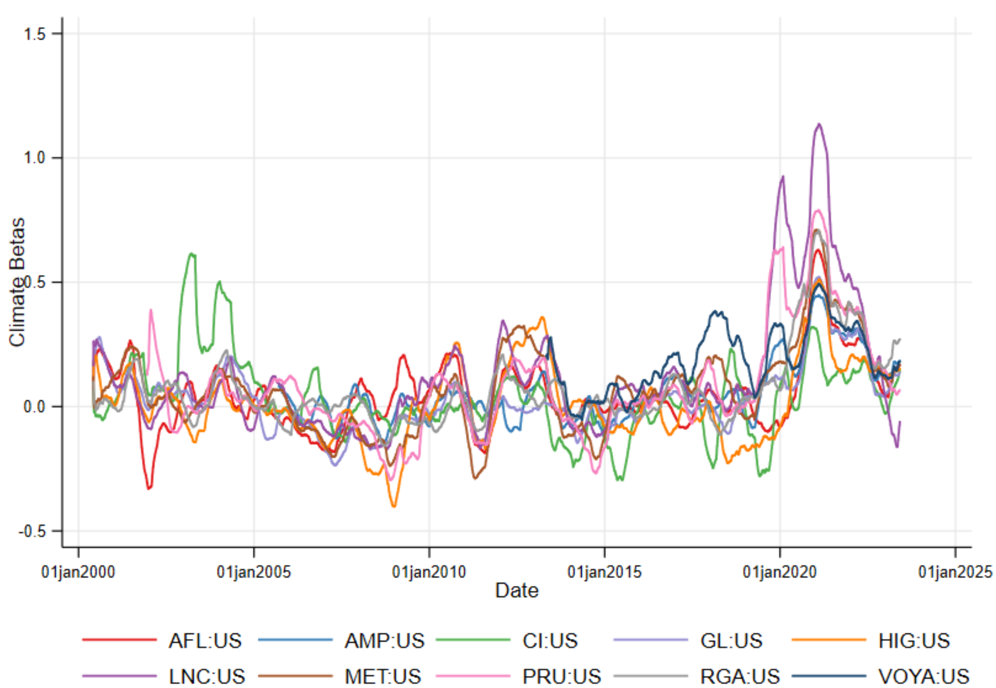
Note: Panel A displays the physical climate beta of P&C insurers in the U.S.. Panel B exhibits the transition climate beta of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in the U.S. in Table 1. The sample period is from January 2002 to December 2020.

Figure 6: Climate Beta of Life Insurers in the U.S.

(a) Physical Climate Beta



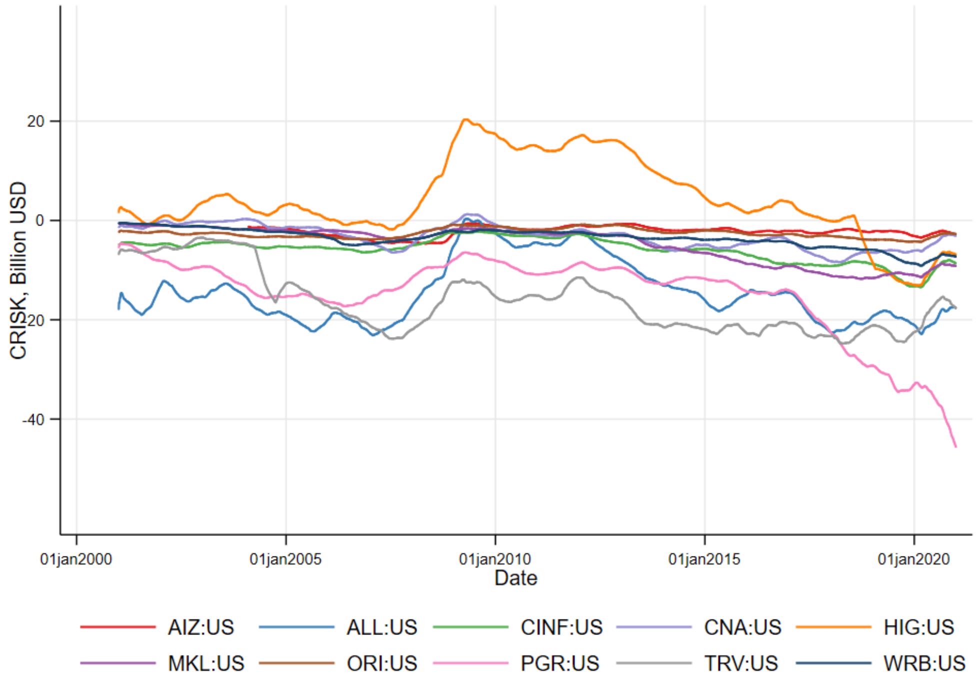
(b) Transition Climate Beta



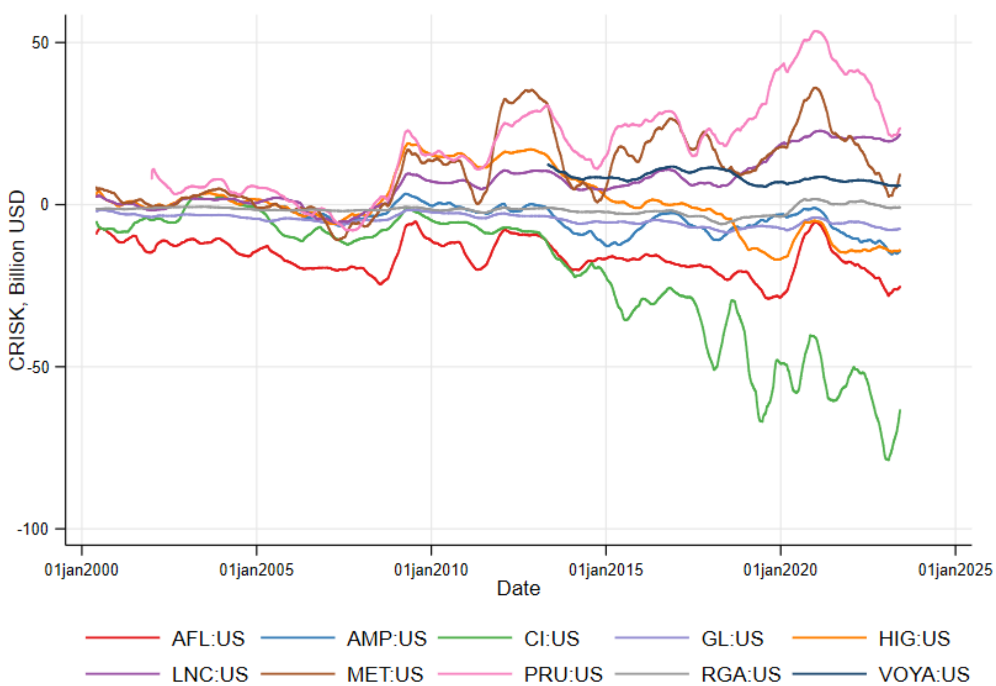
Note: Panel A displays the physical climate beta of life insurers in the U.S.. Panel B exhibits the transition climate beta of life insurers in the U.S.. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

FIGURE 7: CRISK

(A) PHYSICAL CRISK OF P&C INSURERS IN THE U.S.



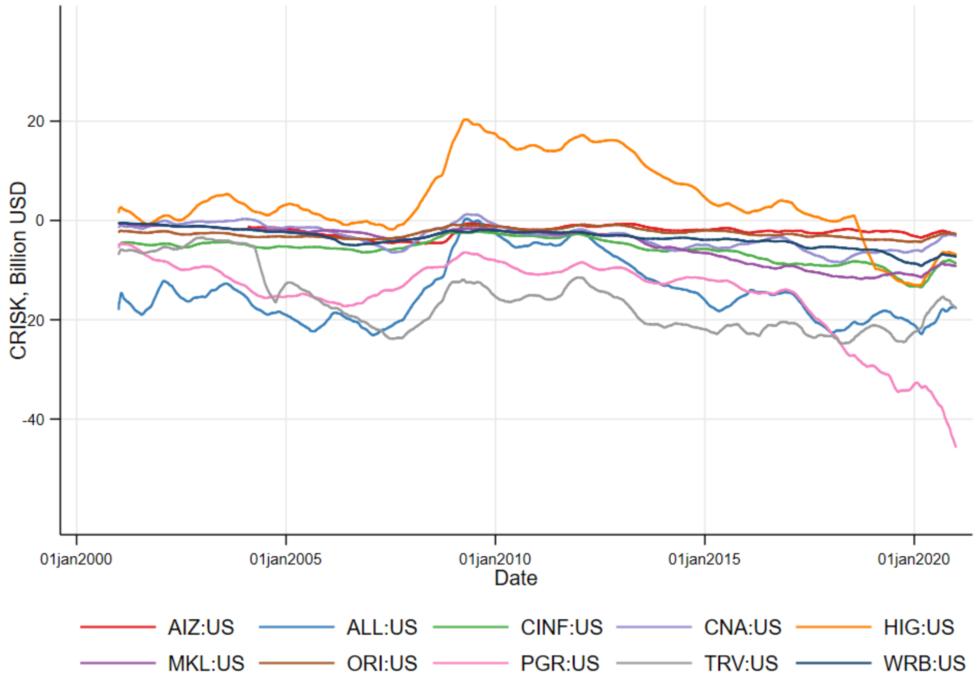
(B) TRANSITION CRISK OF LIFE INSURES IN THE U.S.



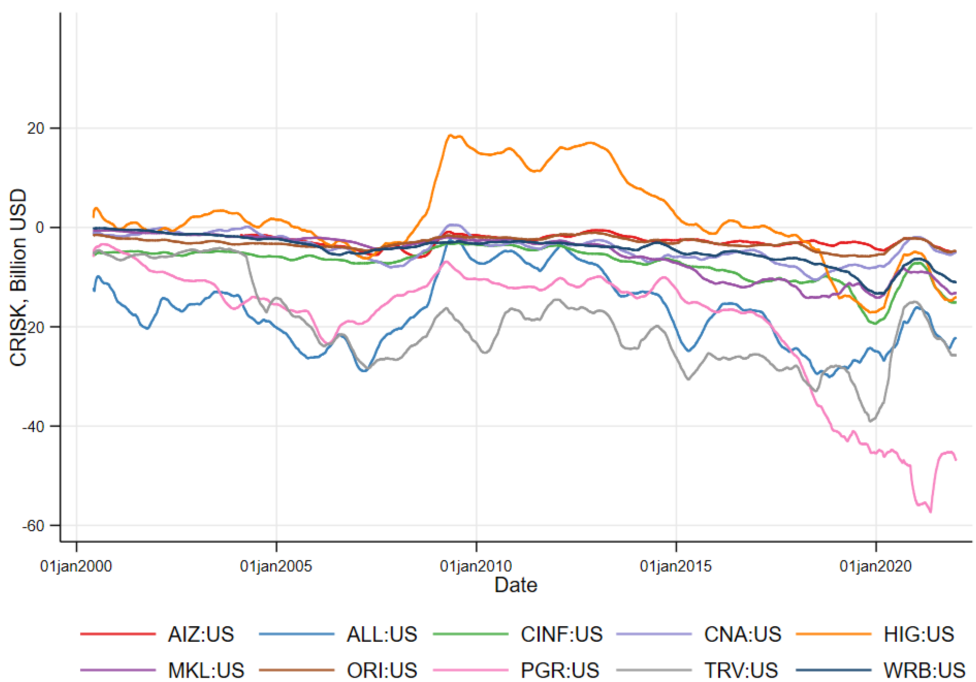
Note: Panel A displays the physical CRISK of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in Table 1. The sample period is from January 2002 to December 2020. Panel B exhibits the transition CRISK of life insurers in the U.S.. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

FIGURE 8: CRISK OF P&C INSURERS IN THE U.S.

(A) PHYSICAL CRISK



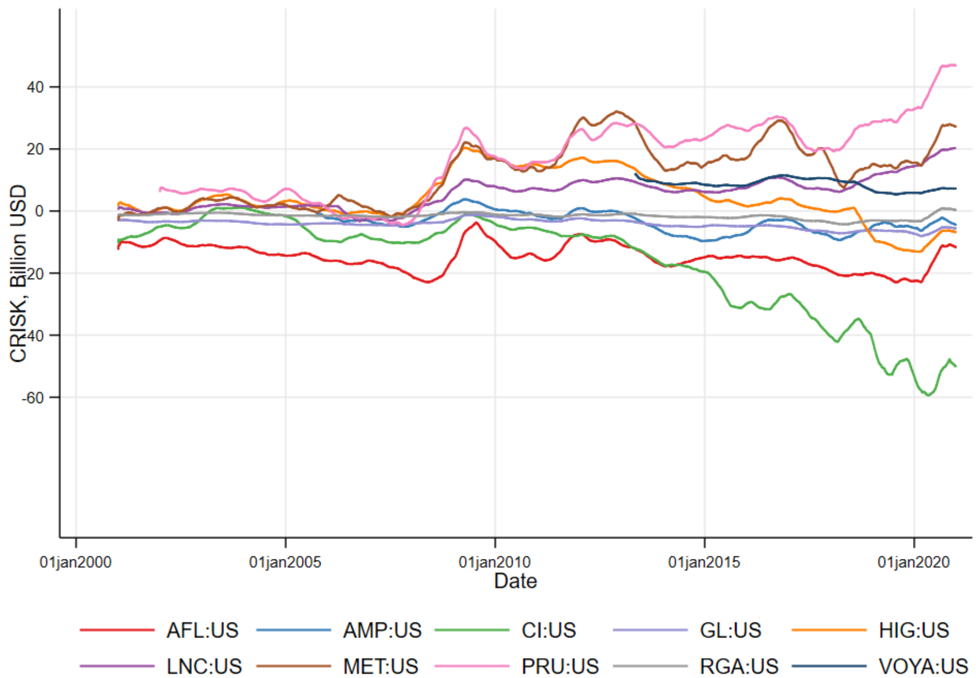
(B) TRANSITION CRISK



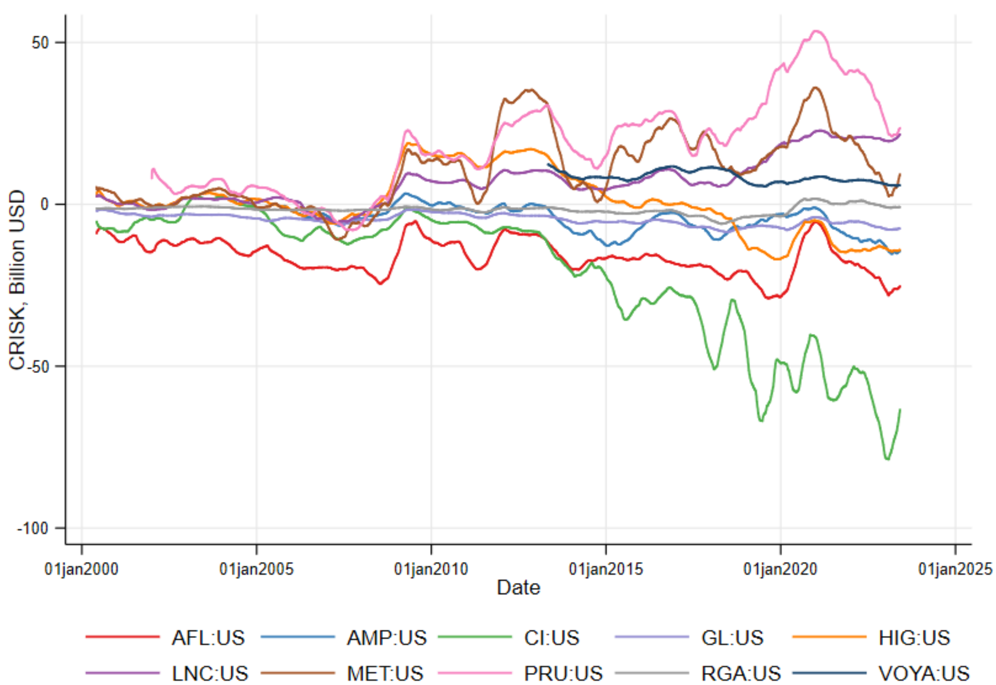
Note: Panel A displays the physical CRISK of P&C insurers in the U.S.. Panel B exhibits the transition CRISK of P&C insurers in the U.S. The sample insurers are the top large P&C insurers in Table 1. The sample period is from January 2002 to December 2020.

FIGURE 9: CRISK OF LIFE INSURERS IN THE U.S.

(A) PHYSICAL CRISK



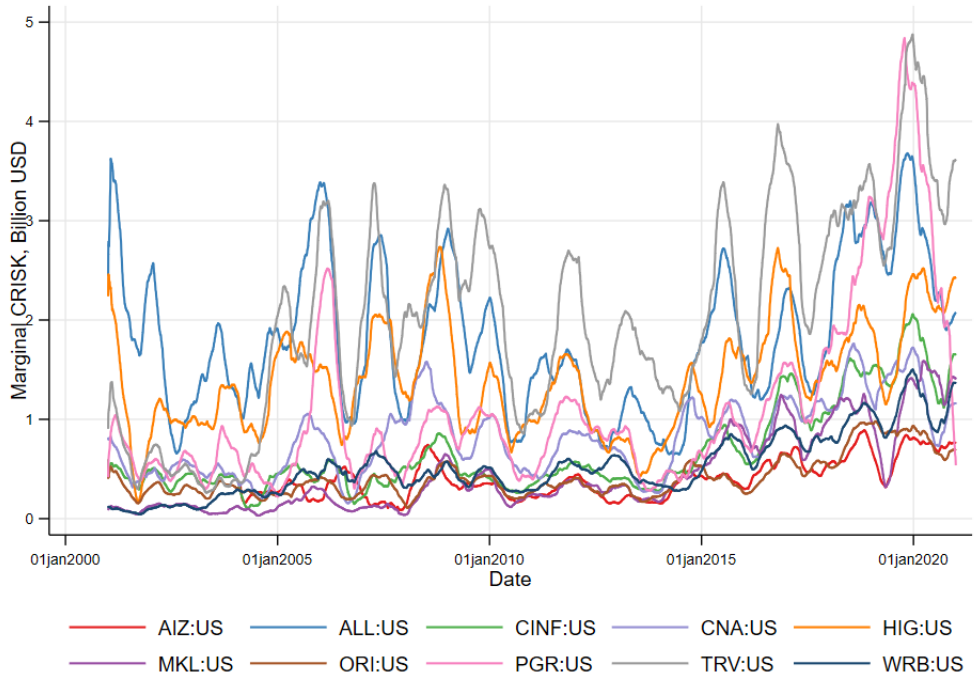
(B) TRANSITION CRISK



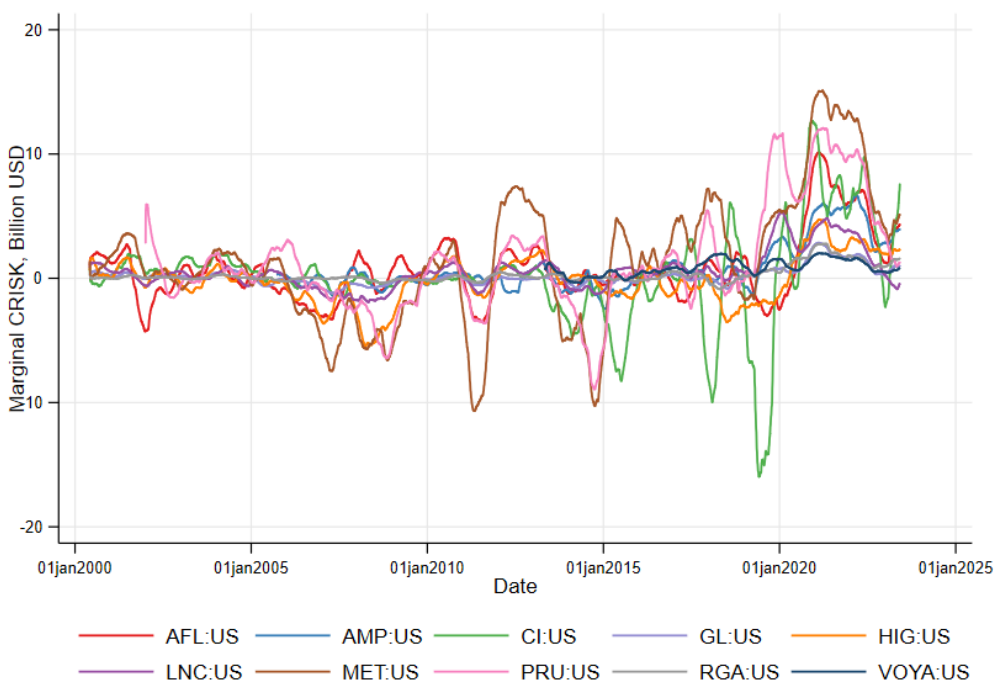
Note: Panel A displays the physical CRISK of life insurers in the U.S.. Panel B exhibits the transition CRISK of life insurers in the U.S. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

FIGURE 10: MARGINAL CRISK

(A) PHYSICAL MARGINAL CRISK OF P&C INSURERS IN THE U.S.



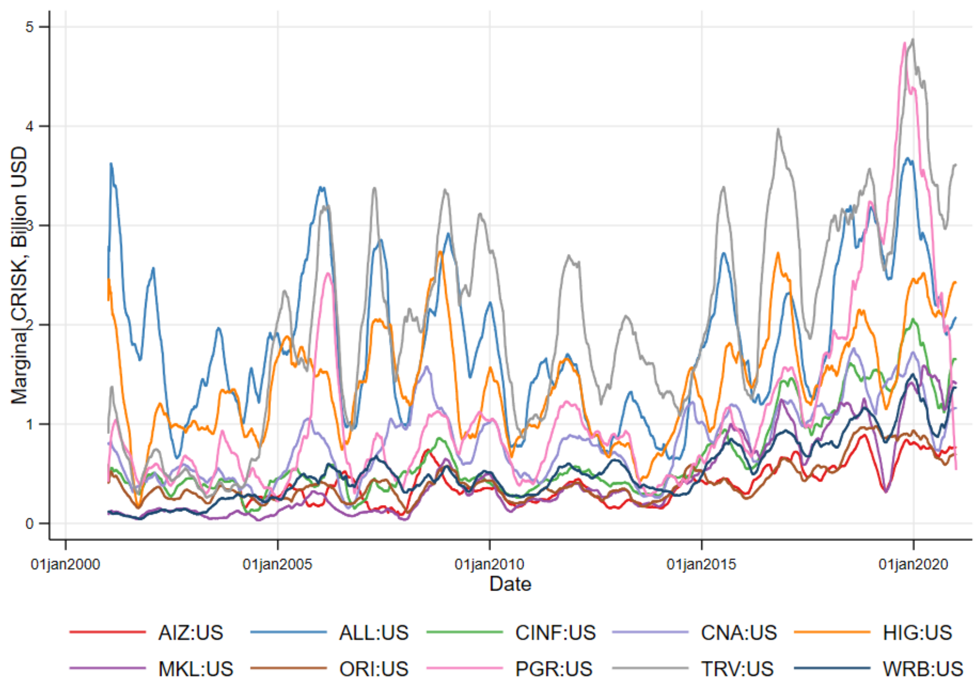
(B) TRANSITION MARGINAL CRISK OF LIFE INSURES IN THE U.S.



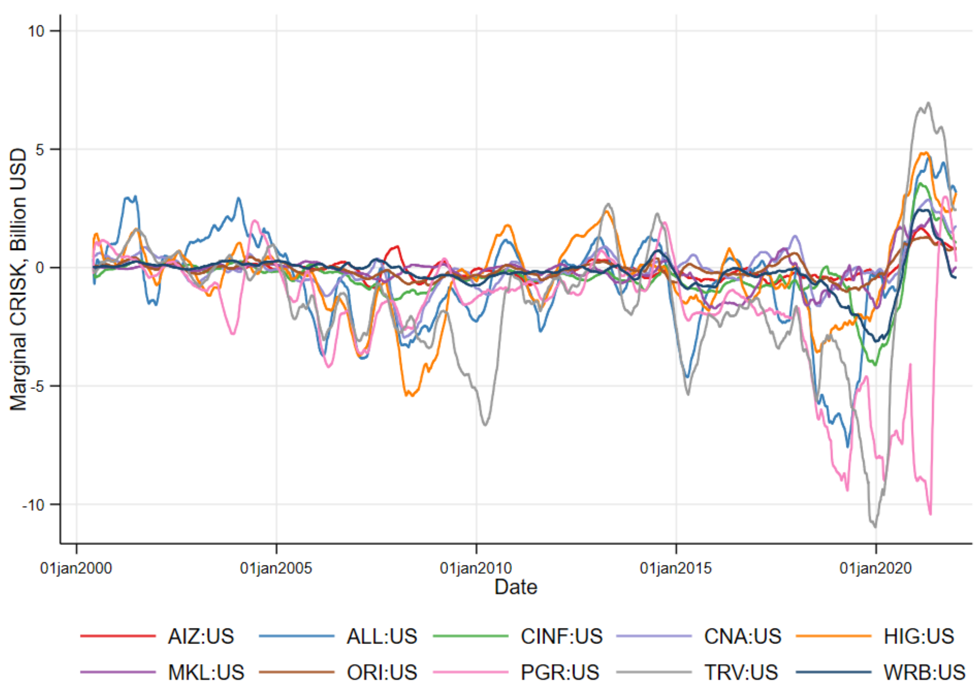
Note: Panel A displays the physical marginal CRISK of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in Table 1. The sample period is from January 2002 to December 2020. Panel B exhibits the transition marginal CRISK of life insurers in the U.S.. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

FIGURE 11: MARGINAL CRISK OF P&C INSURERS IN THE U.S.

(A) PHYSICAL MARGINAL CRISK



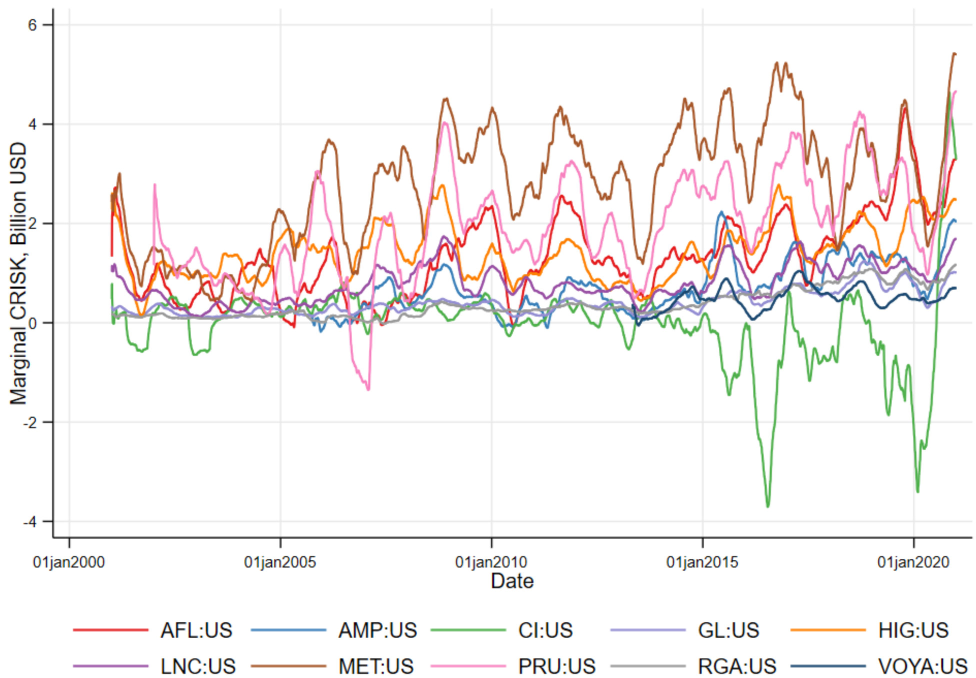
(B) TRANSITION MARGINAL CRISK



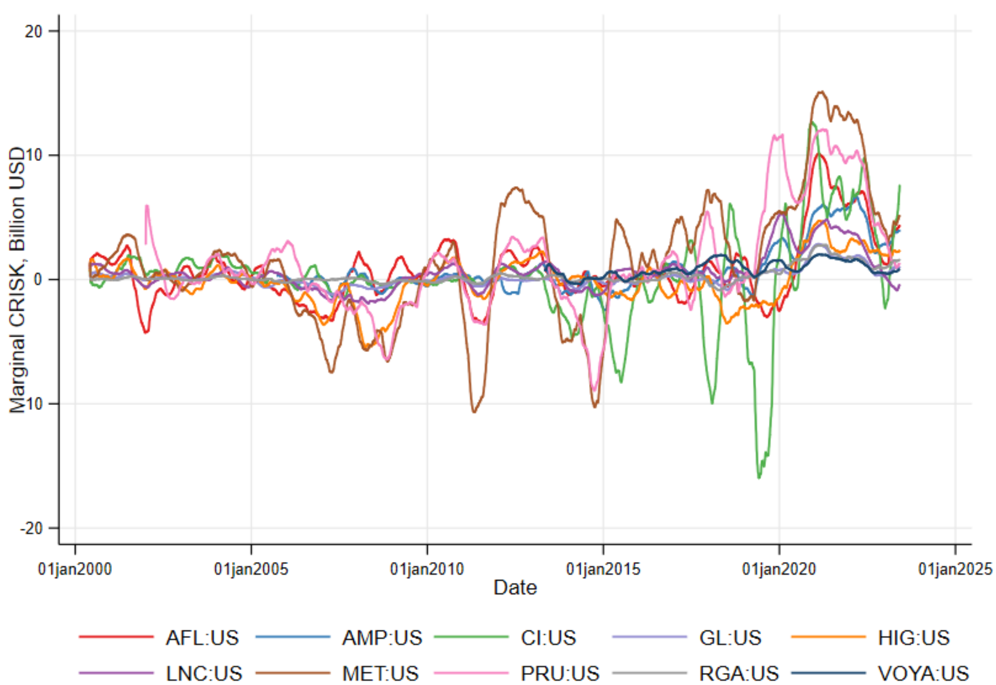
Note: Panel A displays the physical marginal CRISK of P&C insurers in the U.S.. Panel B exhibits the transition marginal CRISK of P&C insurers in the U.S. The sample insurers are the top large P&C insurers in Table 1. The sample period is from January 2002 to December 2020.

Figure 12: Marginal CRISK of Life Insurers in the U.S.

(a) Physical Marginal CRISK

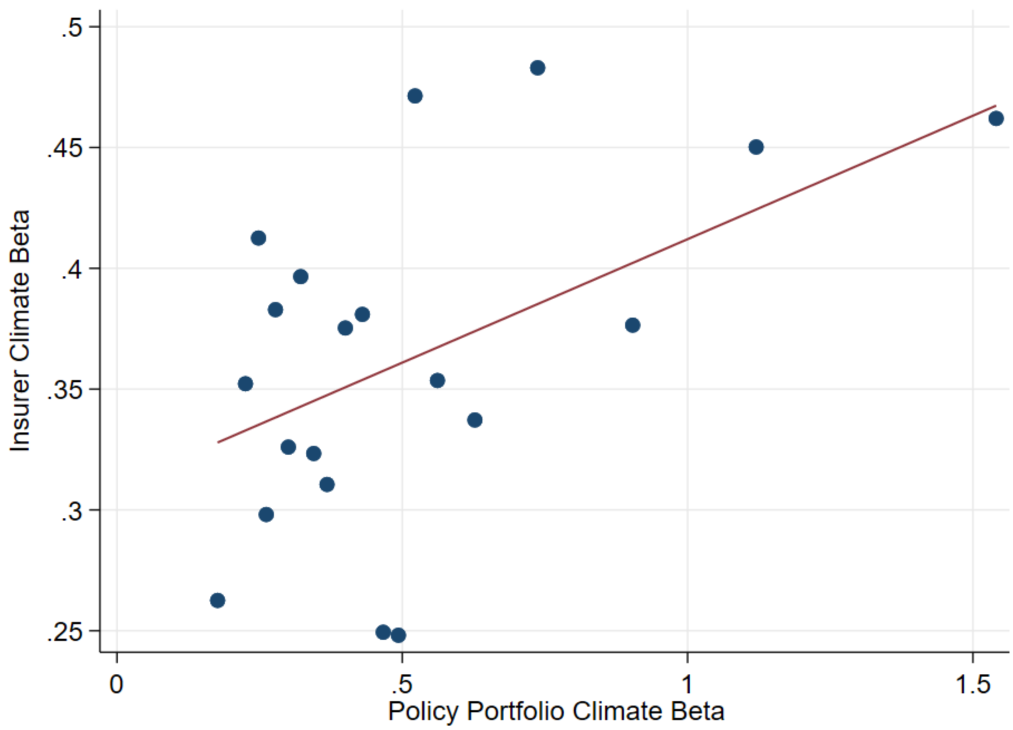


(b) Transition Marginal CRISK



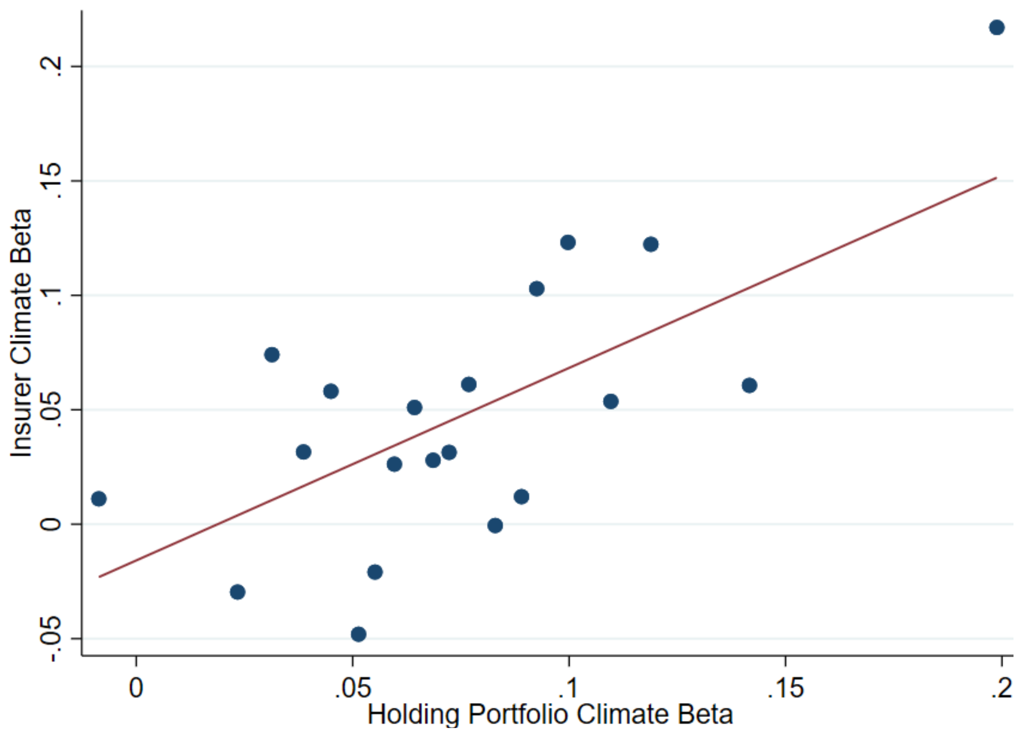
Note: Panel A displays the physical marginal CRISK of life insurers in the U.S.. Panel B exhibits the transition marginal CRISK of life insurers in the U.S. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

FIGURE 13: CORRELATION BETWEEN PHYSICAL CLIMATE BETA AND POLICY PORTFOLIO BETA



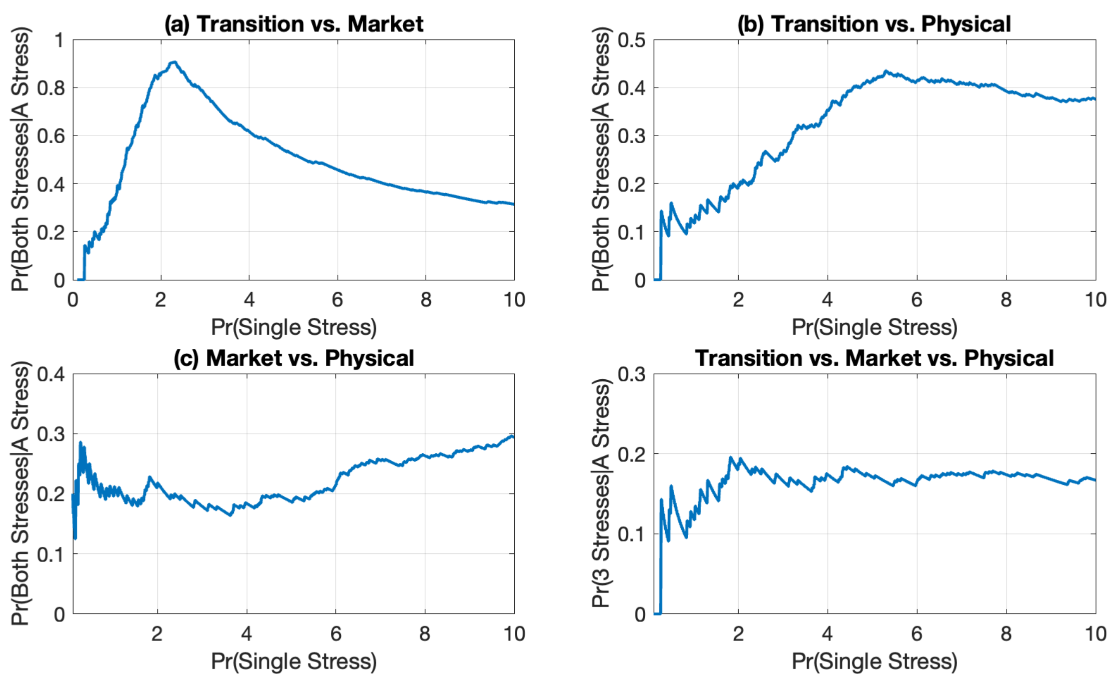
Note: Binned scatter plot of insurer physical climate beta and policy portfolio climate beta without controls and fixed effects, based on annual data from 2005 to 2019 for listed P&C Insurers in the U.S.

FIGURE 14: CORRELATION BETWEEN TRANSITION CLIMATE BETA AND BOND PORTFOLIO BETA



Note: Binned scatter plot of insurer transition climate beta and bond portfolio climate beta without controls and fixed effects, based on annual data from 2000 to 2020 for listed Life Insurers in the U.S..

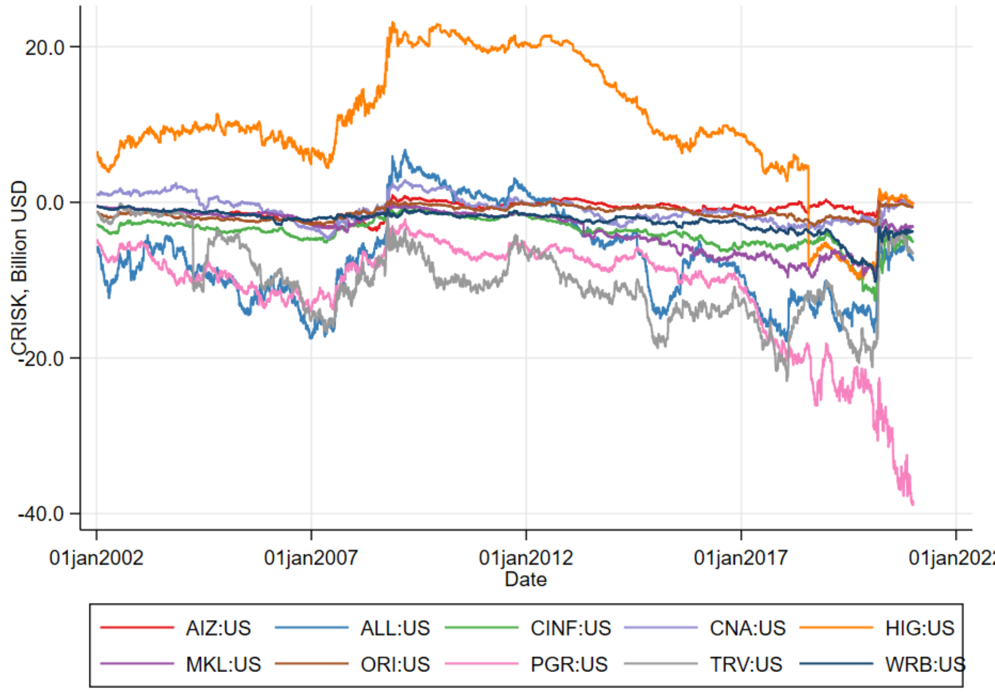
FIGURE 15: TAIL DEPENDENCE



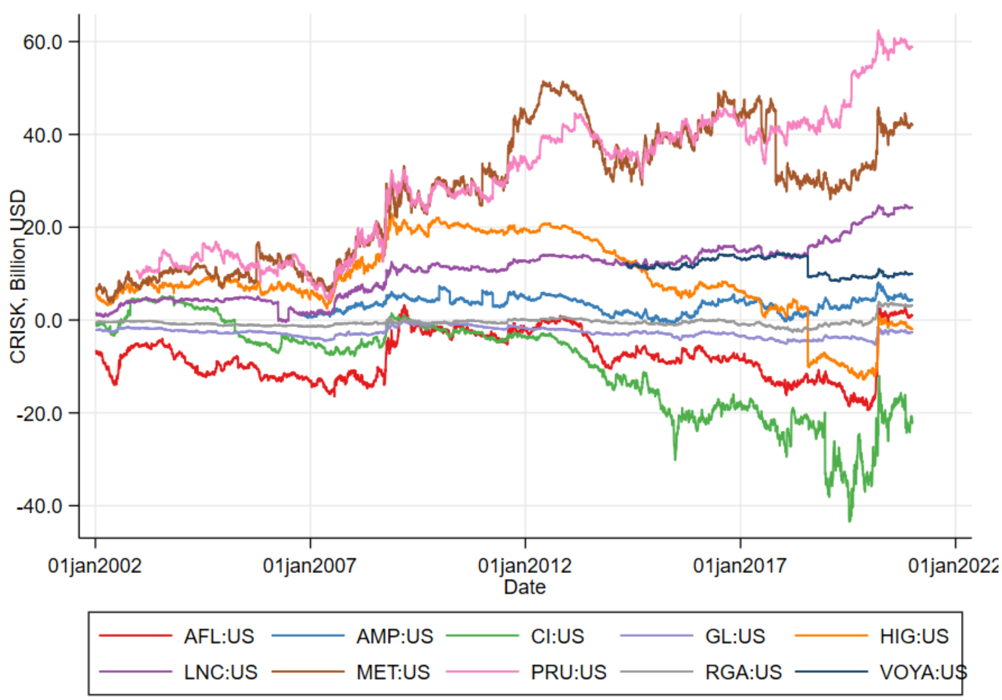
Note: Panels (a), (b), and (c) plot $\lambda(u)$ vs. u, where $u = P(x < -\theta_x) = P(y < -\theta_y) = u$ and $\lambda(u) = P(y < -\theta_y | x < -\theta_x)$. x and y denote two factors, and θ_x and θ_y denote the associated stress levels. u can be interpreted as the probability of single stress event and $\lambda(u)$ can be interpreted as the probability of two (three) stress events conditional on single stress. The sample is based on the 6-month returns on the factors during 2001-2020.

Figure 16: Compound CRISK

(a) Esimated CCRISK of Top 10 P&C Insurers



(b) Esimated CCRISK of Top 10 Life Insurers



Note: Panel A displays the estimated compound CRISK of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in Table 1. The sample period is from January 2002 to December 2020. Panel B exhibits the estimated compound CRISK of life insurers in the U.S.. The sample insurers are the top large life insurers in Table 1. The sample period is from June 2000 to December 2021.

A Additional Tables and Figures

TABLE A.1: SUMMARY STATISTICS OF FACTORS

	mean	sd	p25	p75	count
Market (SPY)	0.0003	0.0123	-0.0041	0.0058	4784
TCF: Stranded Asset	-0.0005	0.0134	-0.0070	0.0068	4784
PCF: Insurer Premium	0.0002	0.0113	-0.0057	0.0059	4784
PCF: Insurer losss-to-equity	0.0001	0.0099	-0.0048	0.0048	4784
PCF: Damage Variance	0.0003	0.0124	-0.0058	0.0060	4784
PCF: Net Damage	0.0002	0.0083	-0.0037	0.0040	4784
Trucost-based	0.0004	0.0043	-0.0020	0.0026	4784

Note: The sample period is 2002-2020 and all factors are daily.

TABLE A.2: CORRELATION OF FACTORS

Panel A: Pearson Factor Correlations	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Risk Factor							
(1) SPY ETF	1.00						
Transition Risk Factor							
(2) Stranded Asset	0.22	1.00					
Physical Risk Factor							
(3) Insurer Premium	0.02	0.02	1.00				
(4) Losss-to-Equity	0.05	0.01	0.77	1.00			
(5) Damage Variance	0.11	0.05	0.85	0.81	1.00		
(6) Net Damage	0.09	0.02	0.80	0.83	0.77	1.00	
(7) Trucost-based	0.32	0.15	0.15	0.15	0.16	0.16	1.00

Panel B: Orthogonalizd to Fama-French Three Factors	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Market Risk Factor							
(1) SPY ETF	1.00						
Transition Risk Factor							
(2) Stranded Asset	-0.11	1.00					
Physical Risk Factor							
(3) Insurer Premium	0.01	-0.10	1.00				
(4) Losss-to-Equity	0.03	-0.13	0.68	1.00			
(5) Damage Variance	0.03	-0.09	0.80	0.75	1.00		
(6) Net Damage	-0.01	-0.16	0.75	0.76	0.70	1.00	
(7) Trucost-based	-0.15	0.03	0.01	0.03	-0.00	0.06	1.00

Note: Panel A shows the daily factor correlations for the period 2002 to 2020. Panel B shows the corresponding factor correlations after orthogonalizing each factor with respect to the Fama-French market, size and value factors.

TABLE A.3: CORRELATION OF BETAS

Panel A: Pearson Insurer Climate Beta Correlations	(1)	(2)	(3)	(4)	(5)	(6)
Transition Risk Factor						
(1) Stranded Asset	1.00					
Physical Risk Factor						
(2) Insurer Premium	0.49	1.00				
(3) Losss-to-Equity	0.34	0.85	1.00			
(4) Damage Variance	0.56	0.97	0.85	1.00		
(5) Net Damage	0.46	0.90	0.94	0.89	1.00	
(6) Trucost-based	0.80	0.32	0.16	0.34	0.27	1.00

Panel B: Spearman (Rank) Insurer Climate Beta Correlations	(1)	(2)	(3)	(4)	(5)	(6)
Transition Risk Factor						
(1) Stranded Asset	1.00					
Physical Risk Factor						
(2) Insurer Premium	0.45	1.00				
(3) Losss-to-Equity	0.54	0.84	1.00			
(4) Damage Variance	0.56	0.97	0.89	1.00		
(5) Net Damage	0.61	0.87	0.88	0.90	1.00	
(6) Trucost-based	0.35	0.27	0.21	0.29	0.36	1.00

Note: Panel A shows the Pearson correlations among the insurer-specific climate betas. Panel B shows the Spearman rank correlation among the insurer-specific climate betas. The coefficients $\beta^1_{i,t}$ are based on estimating $Ret_{i,t} = \beta_0 + \beta^1_{i,t} CF_t + \beta^2_{i,t} MKT_t + \epsilon_{i,t}$, where $Ret_{i,t}$ denotes the return of insurer i on date t, CF_t is one of the six climate risk factors on date t and MKT_t controls for the market factor. The $\beta^1_{i,t}$s are estimated using data from 2001 to 2020 inclusive.

TABLE A.4: NEW YORK TIMES ARTICLES ON HURRICANE KATRINA

Date	Article Title
8/26/2005	A Blast of Rain but Little Damage as Hurricane Hits South Florida
8/27/2005	Hurricane Drenches Florida And Leaves Seven Dead
8/29/2005	Approaching Storm Slows Oil Output in Gulf of Mexico
8/29/2005	POWERFUL STORM THREATENS HAVOC ALONG GULF COAST
8/29/2005	With Few Warning Signs, an Unpredictable Behemoth Grew
8/29/2005	In Slot Machines' Silence, A Storm's Economic Cost
8/30/2005	Nature's Revenge
8/30/2005	Another Storm Casualty: Oil Prices
8/30/2005	Shares Rally as Oil Prices Pull Back From Early Surge
8/30/2005	Storms Vary With Cycles, Experts Say
8/30/2005	Escaping Feared Knockout Punch, Barely, New Orleans Is One Lucky Big Mess
8/30/2005	Guard Units' New Mission: From Combat To Flood Duty
8/30/2005	After Centuries of 'Controlling' Land, Gulf Residents Learn Who's Really the Boss
8/30/2005	HURRICANE SLAMS INTO GULF COAST; DOZENS ARE DEAD
8/30/2005	In Coastal City, Ruin All Around
8/30/2005	Insurers Estimate Damage at $9 Billion, Among Costliest U.S. Storms on Record
8/31/2005	Navy Ships and Maritime Rescue Teams Are Sent to Region
8/31/2005	NEW ORLEANS IS INUNDATED AS 2 LEVEES FAIL; MUCH OF GULF COAST IS CRIPPLED; TOLL RISES
8/31/2005	New York City Looks South For Lessons a Storm Can Teach
8/31/2005	No Quick Fix for Gulf Oil Operations
8/31/2005	Payouts Hinge on the Cause of Damage
8/31/2005	The Misery Is Spread Equally
8/31/2005	Where Living at Nature's Mercy Had Always Seemed Worth the Risk
8/31/2005	Casino Owners Look Toward Rebuilding
8/31/2005	Damage to Economy Is Deep and Wide
8/31/2005	Disease and Coordination Vie as Major Challenges
8/31/2005	Face to Face With Death and Destruction in Biloxi
8/31/2005	Flooding Stops Presses and Broadcasts, So Journalists Turn to the Web
8/31/2005	Geography Complicates Levee Repair

8/31/2005 In Search of a Place to Sleep, and News of Home
8/31/2005 Life-or-Death Words of the Day in a Battered City: 'I Had to Get Out'
8/31/2005 Markets Assess Hurricane Damage, and Shares Fall
9/1/2005 Millions Said to Be Lacking Phone Service of Any Kind
9/1/2005 A City in Ruins: Americans Open Their Hearts
9/1/2005 Oil and Construction IssuesLead Shares Broadly Higher
9/1/2005 Administration Steps Up Actions, Adding Troops and Dispatching Medical Supplies
9/1/2005 Rows and Rows of Corpses, And Voices Choked With Sobs
9/1/2005 Searching for the Living, but Mostly Finding the Dead
9/1/2005 Television Finds Covering Area Hit by Storm Is Like Working in a War Zone
9/1/2005 Utility Workers Come From Afar to Help Their Brethren Start Restoring Service
9/1/2005 Waiting for a Leader
9/1/2005 Wall of Water Set a Record
9/1/2005 At Stadium, a Haven Quickly Becomes an Ordeal
9/1/2005 BUSH SEES LONG RECOVERY FOR NEW ORLEANS; 30,000 TROOPS IN LARGEST U.S. RELIEF EFFORT
9/1/2005 Deal Is Put Off For Louisiana Bank
9/1/2005 Economy's Pace Is Lowered a Bit
9/1/2005 Educators Offer Classrooms To Many Displaced Students
9/1/2005 GAS PRICES SURGE AS SUPPLY DROPS
9/1/2005 Hazards Contained in Waters Are Not as Toxic as Feared
9/1/2005 Intricate Flood Protection Long a Focus of Dispute
9/1/2005 Loved Ones Turn to Web For Searches In Flood Zone
9/2/2005 Mississippi's Morning After
9/2/2005 New Orleans Is Awaiting Deliverance
9/2/2005 Rotting Food, Dirty Water And Heat Add to Problems
9/2/2005 Spanning the Gulf
9/2/2005 The Man-Made Disaster
9/2/2005 They Saw It Coming
9/2/2005 A Can't-Do Government
9/2/2005 You Want How Much a Gallon?
9/2/2005 Anxious Liberal Groups Try to Rally Opposition Against Supreme Court Nominee
9/2/2005 As One City Is Emptying, Another Finds Itself Full

9/2/2005	A Desperate Search for Relief, and for Answers
9/2/2005	By Air or Car, Travel Is Complex
9/2/2005	Cameras Captured a Disaster But Now Focus on Suffering
9/2/2005	Conservation? It's Such A 70's Idea
9/2/2005	Democrats and Others Criticize White House's Response to Disaster
9/2/2005	DESPAIR AND LAWLESSNESS GRIP NEW ORLEANS AS THOUSANDS REMAIN STRANDED IN SQUALOR
9/2/2005	From Margins of Society to Center of the Tragedy
9/2/2005	Gazing at Breached Levees, Critics See Years of Missed Opportunities
9/2/2005	Government Saw Flood Risk but Not Levee Failure
9/2/2005	In a Multitude of Forms, the Offers of Help Pour In
9/3/2005	Newcomer Is Struggling to Lead a City in Ruins
9/3/2005	On Ruined Coast, the Desperate Cry Out for Loved Ones Still Lost
9/3/2005	Promises by Bush Amid the Tears
9/3/2005	Spotlight on a Hurricane, and Off the Mayoral Race
9/3/2005	Spot Shortages Of Gas Reported Around Country
9/3/2005	United States Of Shame
9/3/2005	Bus Full of Evacuees Crashes, Leaving 1 Dead and 17 Hurt
9/3/2005	Closed to Visitors
9/3/2005	First Estimate Puts Storm's Economic Toll at $100 Billion
9/3/2005	Indictments and Statistics All Overwhelmed by Tragedy Down South
9/3/2005	In First Response to Crisis, Bush Strikes Off-Key Notes
9/3/2005	Job Growth Stepped Up Its Pace In August
9/3/2005	Katrina's Assault on Washington
9/3/2005	Lawmakers Criticize U.S. Response
9/3/2005	Military Dealt With Combination of Obstacles Before Reaching Victims
9/3/2005	MORE TROOPS AND AID REACH NEW ORLEANS; BUSH VISITS AREA; CHAOTIC EXODUS CONTINUES
9/4/2005	Falluja Floods the Superdome
9/4/2005	Homeland Security Chief Defends Federal Response
9/4/2005	Katrina's Shock to the System
9/4/2005	Legislative Agenda Turned Upside Down by Hurricane
9/4/2005	Navy Turns to Halliburton For Help on Damaged Bases
9/4/2005	Police Quitting, Overwhelmed by Chaos
9/4/2005	Storm Is Devastating for Businesses in Gulf Area, but Its National Effect Remains Muted

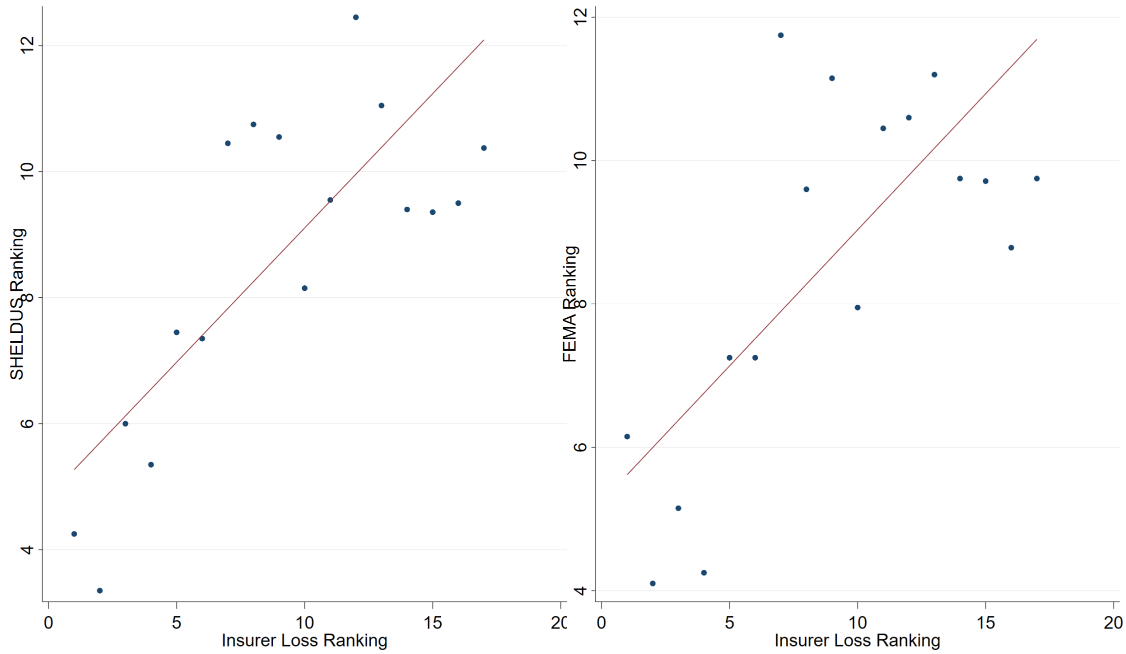
9/4/2005	Storm Will Have a Long-Term Emotional Effect on Some, Experts Say
9/4/2005	As Anxiety Over Storm Increases, Bush Tries to Quell Political Crisis
9/4/2005	The View From Abroad
9/4/2005	With Mayor on Roll and Minds on Gulf, Democrats Hone Final Tactics
9/4/2005	A Delicate Balance Is Undone in a Flash, and a Battered City Waits
9/4/2005	Bush Pledges More Troops as the Evacuation Grows
9/4/2005	Career-Maker For Williams As the Anchor At NBC
9/5/2005	Not Even Web Retailers Will Be Exempt From the Aftereffects of Katrina
9/5/2005	On the Gulf Coast, a Chance to Inspire Is Slipping Away
9/5/2005	Reporting, and Living Out, a Calamity
9/5/2005	Amid Criticism of Federal Efforts, Charges of Racism Are Lodged
9/5/2005	Amid the Ruins, Worshipers Pause to Pray and Receive Messages of Hope
9/5/2005	The Hurricane and Accountability
9/5/2005	The Pendulum Of Reporting On Katrina
9/5/2005	White House Enacts a Plan To Ease Political Damage
9/5/2005	A 'Weather Nerd' in Indiana Sent a Warning to the Mayor
9/5/2005	BUSH PROMISES TO MOVE QUICKLY ON CHIEF JUSTICE
9/5/2005	Chaotic Week Leaves Bush Team on Defensive
9/5/2005	For Victims, News About Home Can Come From Strangers Online
9/5/2005	Fox Says U.S. Shares Blame For Problems Along Border
9/5/2005	Housing Boom May Continue After Storm, Experts Say
9/5/2005	Hurricane Response Becomes Issue in Mayor's Race
9/5/2005	In Tale of Two Families, a Chasm Between Haves and Have-Nots
9/5/2005	After Failures, Officials Play Blame Game
9/5/2005	Medical Team From Georgia, Trying to Provide Help, Hits Roadblocks Along the Way
9/5/2005	New Orleans Begins a Search for Its Dead
9/6/2005	Mayoral Race Seems Recharged at Parade
9/6/2005	A Hospital Takes In The Tiniest Of Survivors
9/6/2005	Practicing Medicine In the Dark, On the Edge
9/6/2005	PRESIDENT NAMES ROBERTS AS CHOICE FOR CHIEF JUSTICE
9/6/2005	'Prison City' Shows a Hospitable Face to Refugees From New Orleans
9/6/2005	Residents Of a Parish Encountering Lost Dreams
9/6/2005	Scouring the Neighborhoods in a Personal Appeal to Holdouts
9/6/2005	The Larger Shame
9/6/2005	Thrown Off Schedule

9/6/2005	Utility Crews Help Turn Lights Back On in Parts of the Gulf Region
9/6/2005	With Some Now at Breaking Point, City's Officers Tell of Pain and Pressure
9/6/2005	Bush and the Lightning Nomination
9/6/2005	Bush Makes Return Visit; 2 Levees Secured
9/6/2005	Buying Time With Quick Action on the Court and a Second Trip to the South
9/6/2005	Carnival Forecasts Profit Cut From Katrina
9/6/2005	Clinton Is an Unexpected Partner in the Hurricane Effort
9/6/2005	Crawfish Etouffee Goes Into Exile
9/6/2005	Destruction on Mississippi River Delta Illustrates Danger of Life at Earth's Edge
9/6/2005	Filling a Desperate Need for Shelter Begins With Cruise Ships and Proposals
9/6/2005	From the Air, Scientists Comb a Ruined Coastline for Clues and Lessons
9/6/2005	Her Hometown Destroyed, A Traveler Turns to a Blog
9/6/2005	High-Tech Flood Control, With Nature's Help
9/6/2005	Houston Finds Business Boon After Katrina
9/6/2005	In New Orleans, the Business Haves and Have-Nots
9/6/2005	Katrina and the Gas Pump
9/7/2005	Across Nation, Storm Victims Crowd Schools
9/7/2005	Osama and Katrina
9/7/2005	Pain Now, but Gain May Lie Ahead for Gulf Utility
9/7/2005	Putting Down New Roots on More Solid Ground
9/7/2005	School Routine Provides Welcome Change From Chaos
9/7/2005	Shares Up Sharply, Aided by Oil Price and Services Data
9/7/2005	Some Senators on Panel Ask Angry Questions About Gasoline Pricing and Profits
9/7/2005	Ad-Libbing Many Routes, Ships Return To the River
9/7/2005	Urban Evacuees Find Themselves Among Rural Mountains
9/7/2005	Urgent Warning Proved Prescient
9/7/2005	Bush Promises to Seek Answers To Failures of Hurricane Relief
9/7/2005	FLOODING RECEDES IN NEW ORLEANS; U.S. INQUIRY IS SET
9/7/2005	Gas Prices At Pumps Show Signs Of Easing
9/7/2005	Gonzales Is Mentioned in Court Remarks
9/7/2005	Haunted By Hesitation
9/7/2005	Hurricane's Toll Is Likely to Reshape Bush's Economic Agenda
9/7/2005	In Asia, Low Fuel Prices And Subsidies Lose Ground
9/7/2005	It's Not a 'Blame Game'

9/7/2005	A Sight or a Sound Can Bring 9/11 Flooding Back
9/7/2005	Miller Suffers a Setback Over Expenses
9/7/2005	Navy Pilots Who Rescued Victims Are Reprimanded

Note: The titles of New York Times articles that have at least two sentences contain the word "hurricane" in the article from August 26, 2005 to September 7, 2005. Hurricane Katrina started on August 25, 2005 and ended on August 30, 2005.

FIGURE A.1: INSURERS' OPERATIONAL EXPOSURE TO PHYSICAL RISK VS. REALIZED LOSSES



Note: Binned scatter plot of P&C insurer-level operational exposure to physical risk and incurred losses. P&C insurer-level operational exposure to physical risk is computed as the weighted average "riskiness" of states where the weight is the insurer's operational exposure to the respective state. The "riskiness" of state is proxied by the property damage based on SHELDUS in the left panel and the expected annual loss based on FEMA in the right panel. Both insurer loss and riskiness are scaled by insurers' market capitalization. The sample comprises large P&C insurers, and the data spans from 2000 to 2019.

TABLE A.5: DROP IN INDUSTRY OUTPUT FOR CARBON TAX AND GROWTH RATE SCENARIOS IN JORGENSON ET AL. (2018)

IGEM Industry	\$25 tax, 1% growth	\$25 tax, 5% growth	\$50 tax, 1% growth	\$50 tax, 5% growth
Agriculture	0.009	0.016	0.017	0.028
Oil mining	0.026	0.045	0.049	0.079
Gas mining	0.059	0.097	0.103	0.157
Coal mining	0.163	0.237	0.252	0.338
Nonenergy mining	0.016	0.028	0.028	0.046
Electric utilities	0.047	0.077	0.082	0.124
Gas utilities	0.049	0.087	0.092	0.154
Water and wastewater	0.016	0.026	0.028	0.046
Construction	0.010	0.018	0.018	0.030
Wood and paper	0.015	0.026	0.027	0.045
Nonmetal mineral products	0.022	0.039	0.040	0.068
Primary metals	0.022	0.038	0.040	0.066
Fabricated metal products	0.013	0.022	0.023	0.037
Machinery	0.014	0.024	0.025	0.040
Information technology equipment	0.008	0.013	0.013	0.022
Electrical equipment	0.009	0.015	0.015	0.025
Motor vehicles and parts	0.014	0.024	0.025	0.040
Other transportation equipment	0.006	0.011	0.012	0.019
Miscellaneous manufacturing	0.010	0.017	0.017	0.029
Food, beverage and tobacco	0.006	0.011	0.012	0.019
Textiles, apparel and leather	0.010	0.017	0.019	0.031
Printing and related activities	0.004	0.007	0.008	0.012
Petroleum and coal products	0.042	0.070	0.077	0.123
Chemicals, rubber and plastics	0.012	0.020	0.022	0.035
Wholesale trade	0.006	0.011	0.011	0.018
Retail trade	0.008	0.013	0.013	0.022
Transportation and warehousing	0.027	0.046	0.048	0.079
Publishing, broadcasting, telecommunications	0.005	0.009	0.010	0.015
Software & information technology services	0.008	0.014	0.014	0.023
Finance and insurance	0.006	0.010	0.011	0.017
Real estate and leasing	0.008	0.013	0.015	0.022
Business services	0.008	0.014	0.015	0.024
Educational services	-0.002	-0.004	-0.004	-0.007
Health care and social assistance	0.003	0.006	0.006	0.010
Accommodation and other services	0.007	0.011	0.012	0.020
Other government	0.001	0.001	0.001	0.002

Note: Estimates of decreases in industry output from Table 8 in Jorgenson et al. (2018). All scenarios here assume that the income from the tax is recycled as a lump sum dividend. Estimates are of decreases in industry output from 2015 until 2050.

B Alternative Physical Risk Factors

Damage Variance Factor is similar to the insurer premium factor but focuses explicitly on the unexpected aspect of property damage resulting from natural disasters. To implement this, we calculate the standard deviation of property damage for each state-year, considering a rolling window spanning the last 15 years. For each year, we compute each insurer i's physical risk exposure, denoted RISK, as:

$$RISK_{t,i} = \sum_{s \in S} \left[\left(\frac{DPE_{i,t-1,s}}{\sum_{s \in S} DPE_{i,t-1,s}} \right) * \text{std}(\text{Property Damage}_{t-1,s}) \right] * \frac{1}{ME_{i,t-1}} \tag{24}$$

where $DPE_{i,s}$ denotes the direct premium earned of insurer i in state s, S denotes all the states where insurer i covers in the previous year. std(Property Damage$_{t-1,s}$) denotes the standard deviation of property damage of state s over the past 15 years. We form a portfolio of all U.S. P&C insurers where the weight is $RISK$ and subtract the market return from the portfolio return to obtain the loss deviation factor.

Net Damage Factor measures the absolute risk rather than the relative ones. Following natural disasters, insurers face higher insurance claims but the negative impact might be offset by the adjusted premia or increased demand. To address this concern, we define realized risk as below, which can be positive or negative:

$$\text{Realized Risk}_{t,i} = \sum_{s \in S} \left[\left(\frac{DPE_{i,t-1,s}}{\sum_{s \in S} DPE_{i,t-1,s}} \right) * \text{Property Damage}_{t-1,s} - DPE_{t-1,s,i} \right] * \frac{1}{ME_{t-1,i}} \tag{25}$$

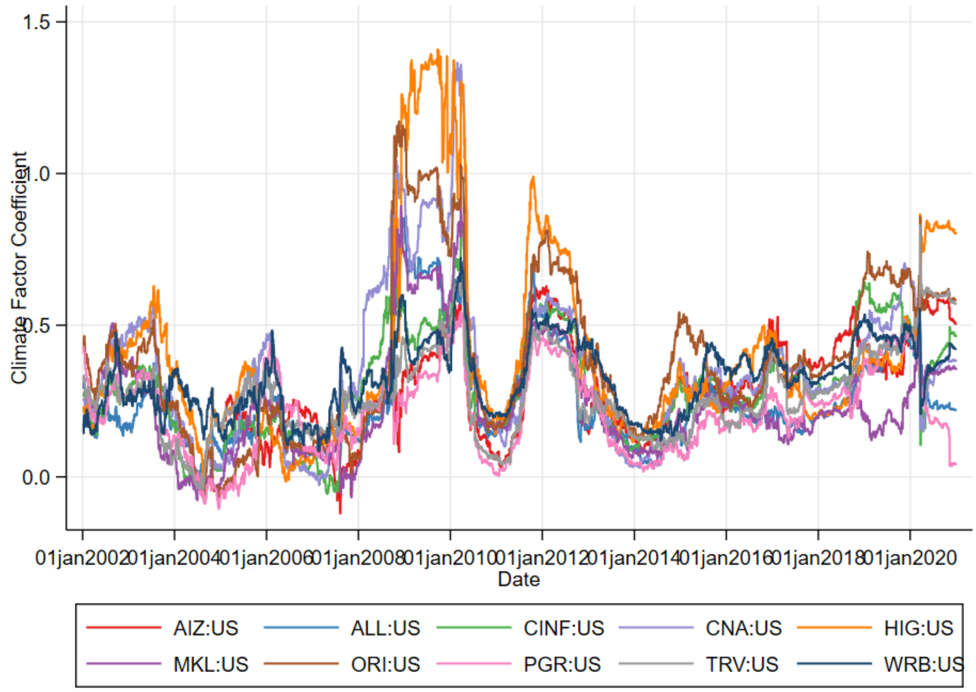
We then construct a long-only portfolio weighted by insurer ranking. Insurers are assigned higher ranks[24] and weights when their realized risk is positive and large relative to market cap. This Net Damage Factor has a variance that rises with climate severity and will be larger when damages are larger, given that the most exposed firms have negative returns.

Trucost-based Factor is constructed from Trucost Climate Change Physical Risk Data. We used a composite physical risk measure, which reflects the expected sensitivity of each company to a combination of seven key climate hazards, including wildfire, fluvial flood, water stress, extreme cold, tropical cyclone, extreme heat, and coastal flood. All risks

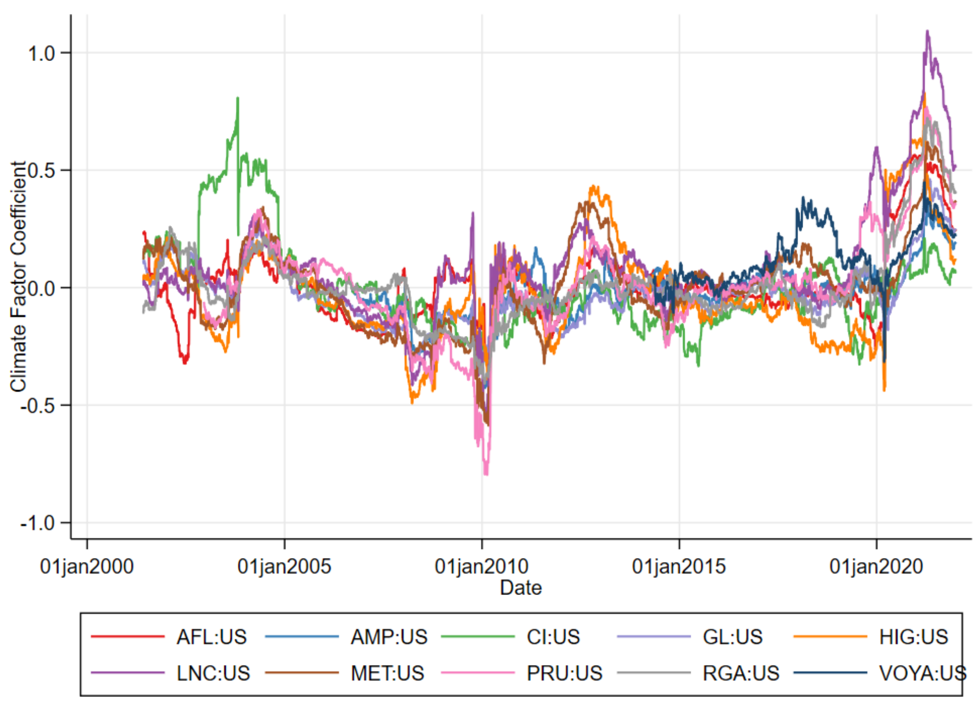
[24] i.e. when there are 30 insurers, the one with the largest positive realized risk relative to market cap ranks 30 and gets assigned a weight of $30 / \sum_{i=1}^{30} i$

FIGURE A.2: CLIMATE BETA AFTER CONTROLLING FOR LTG AND CRD

(A) PHYSICAL CLIMATE BETA



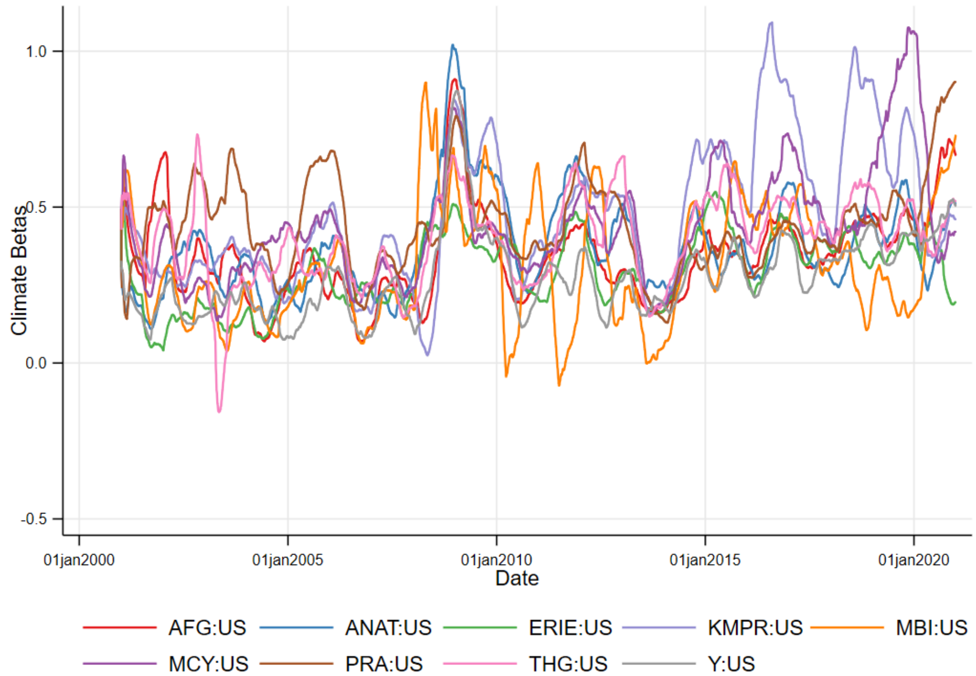
(B) TRANSITION CLIMATE BETA



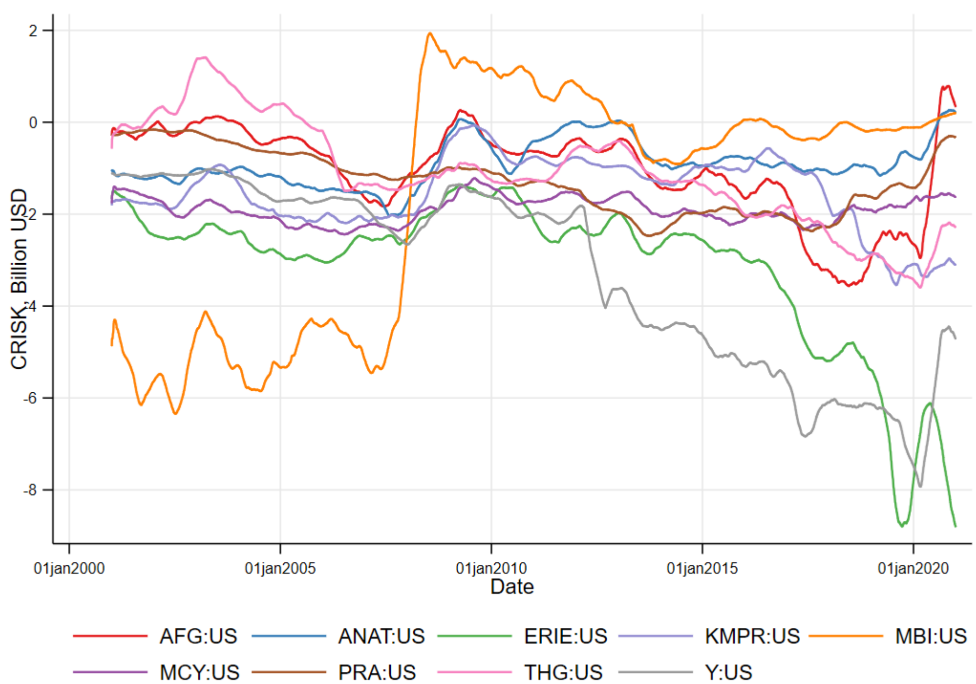
Note: The sample insurers are the top 10 largest US P&C insurers in Table 1. First, we regress insurer stock return on LTG and CRD. Second, we regress the residual from the first step on MKT and PCF and plot the coefficient on CF using 252-day rolling window regression. LTG is log daily return on long-term US government bond index. CRD is log daily return on investment-grade corporate bond index and can be downloaded from Bloomberg. The sample period is from June 2000 to December 2021.

Figure A.3: Physical Climate Beta and CRISK for Small P&C Insurers

(a) Physical Climate Beta



(b) Physical CRISK



Note: Panel A and B display the physical climate beta and physical CRISK of P&C insurers in the U.S.. The sample consists of insurers with market capitalizations exceeding 5 billion USD, excluding those in the top 10 as listed in Table 1. The sample period spans from January 2002 to December 2020.

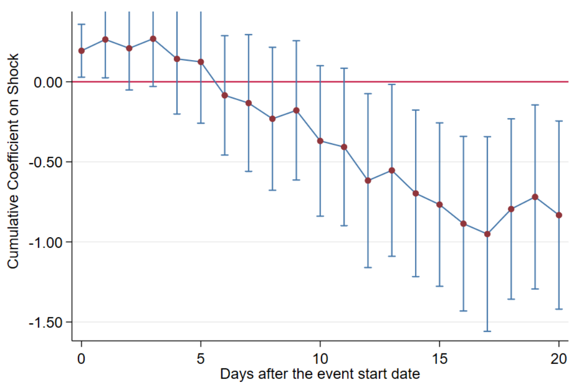
are evaluated based on the High Climate Change Scenario (RCP 8.5 [25]) based on IPCC Representative Concentration Pathways. We sorted firms into ten groups on their physical risk to form a value-weighted long-only portfolio, with a long position in firms within the top decile of physical risk. In the following section, we explore factors evaluated at three future time periods, ranging from short-term (2020), medium-term (2030), to long-term (2050). Appendix Figure A.7 demonstrates the event study of factors' response to physical climate shocks.

[25] Continuation of business as usual with emissions at current rates. This scenario is expected to result in warming in excess of 4 degrees Celsius by 2100.

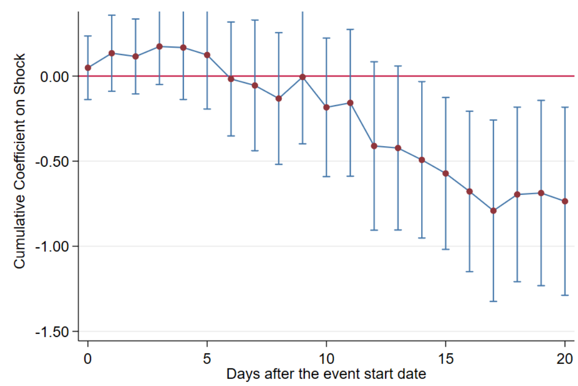
C Physical Risk Factor Event Studies: Robustness Tests

Alternative Physical Risk Factors To assess the robustness of the findings related to the physical risk factors, we constructed four factors using different approaches to compute the $RISK$ variable (See detailed descriptions in and Section 3 and Section B). Appendix Figure A.4 shows that the factors derived through alternative methods for calculating $RISK$ demonstrate comparable responses to natural disaster events.

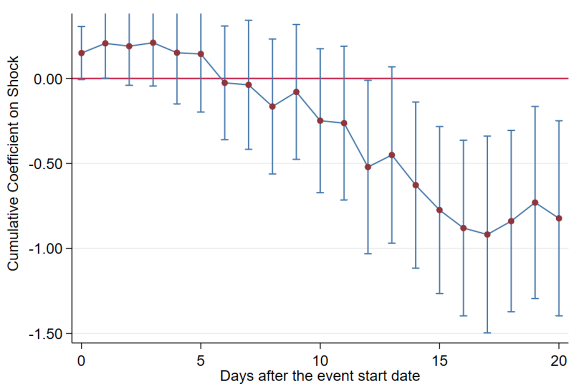
FIGURE A.4: ROBUSTNESS TEST: EVENT STUDY WITH ALTERNATIVE PHYSICAL RISK FACTORS



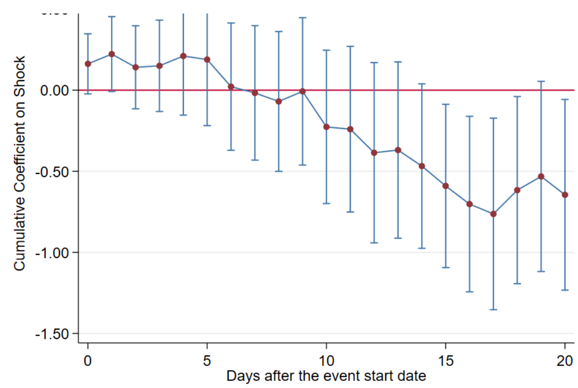
(A) INSURER PREMIUM FACTOR



(B) INSURER LOSS-TO-EQUITY FACTOR



(C) LOSS DEVIATION FACTOR

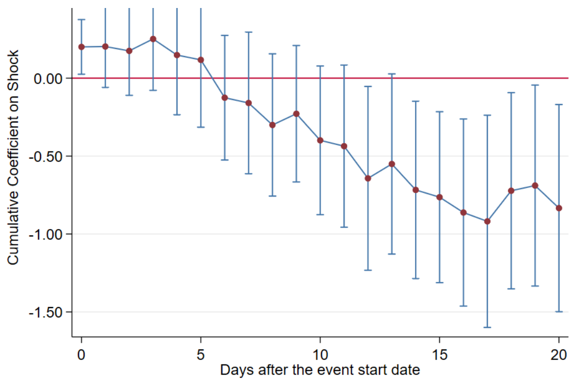


(D) NET DAMAGE FACTOR

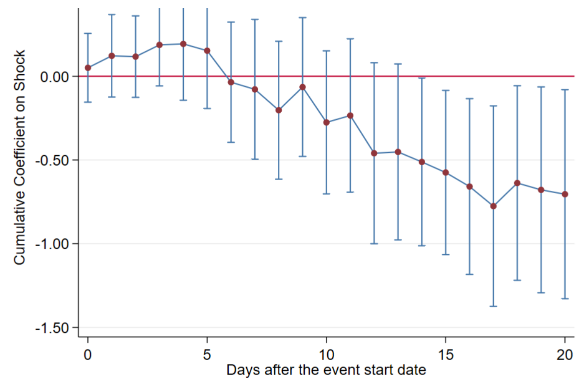
Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$. $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. Each physical risk factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval.

Exclude Flood Events The National Flood Insurance Program underwrites the vast majority of all US flood insurance policies, only under 5% of US flood insurance policies are provided by private insurance underwriters (Ge et al., 2022). Therefore, we conduct a robustness test of our physical risk factors by subtracting property damage caused by flooding in the factor construction and removing flood events in the event study analyses. Appendix Figure A.5 suggests that all four factors decline after natural disaster events and the results are robust after dropping the flood events from the sample.

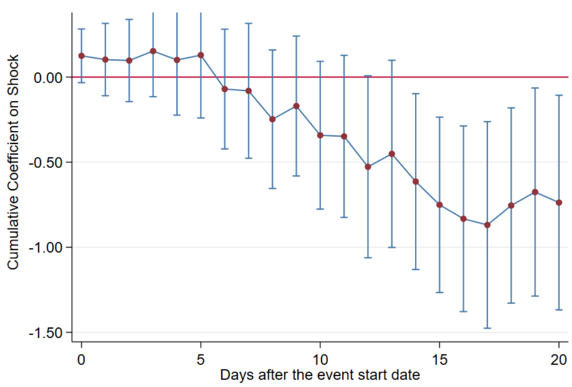
FIGURE A.5: ROBUSTNESS TEST: EVENT STUDY WITHOUT FLOODING



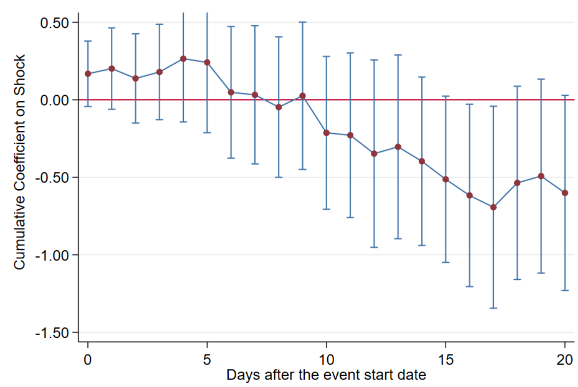
(A) INSURER PREMIUM FACTOR



(B) INSURER LOSS-TO-EQUITY FACTOR



(C) LOSS DEVIATION FACTOR

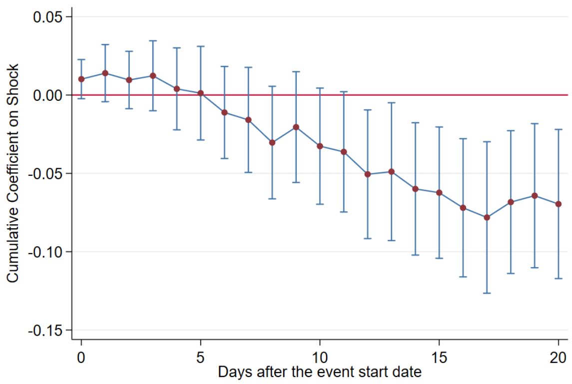


(D) NET DAMAGE FACTOR

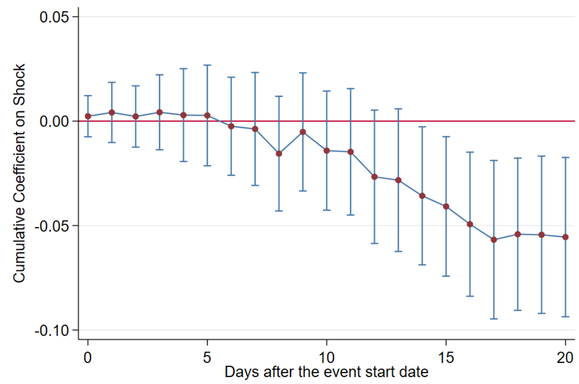
Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$. $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. Each physical risk factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval.

Consider the Size of Losses The responses to natural disaster events can vary depending on their magnitude. For example, smaller events with lower losses may exhibit smaller and slower responses compared to relatively larger events. We conducted a robustness test that takes into account the size of the disaster. In this test, we redefine our variable of interest as "$shock$," which is represented as the log of the loss incurred on the start date of the disaster rather than using a binary value of 1. Notably, Appendix Figure A.6 continues to demonstrate consistency even with this modified approach.

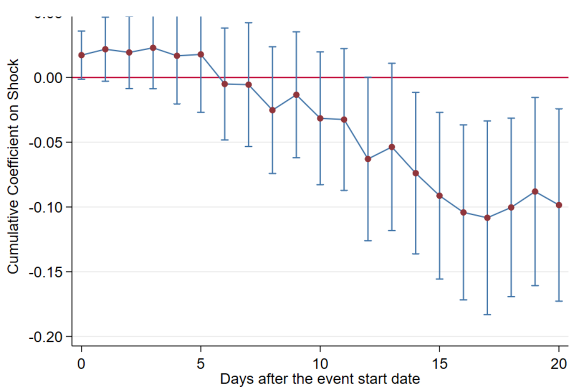
FIGURE A.6: ROBUSTNESS TEST: EVENT STUDY WITH DAMAGE SIZE



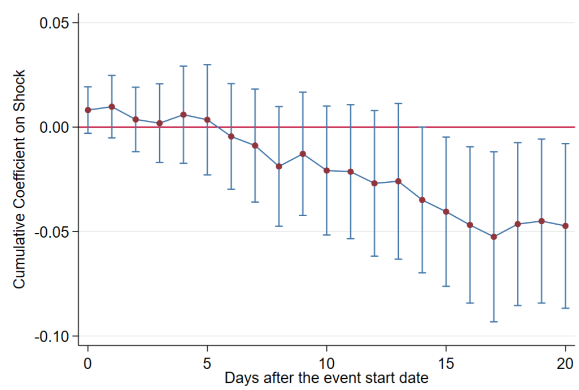
(A) INSURER PREMIUM FACTOR



(B) INSURER LOSS-TO-EQUITY FACTOR



(C) LOSS DEVIATION FACTOR



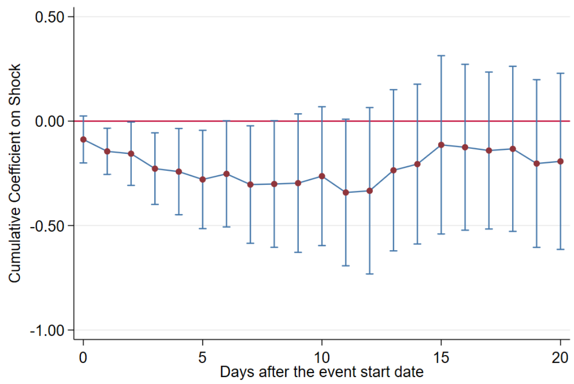
(D) NET DAMAGE FACTOR

Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$. $shock_t$ takes the log value of loss if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. Each physical risk factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval.

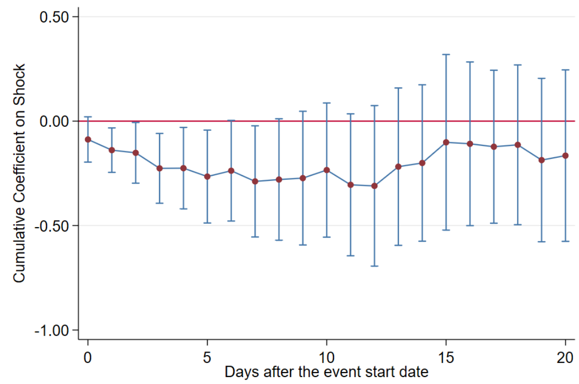
Consider the Time Horizon of Physical Risks The time horizon of physical risk realization remains undetermined. Stroebel and Wurgler (2021) highlight that investors view physical risks as the top risk over the next 30 years. Climate stress tests by central banks, as outlined by Acharya et al. (2023), encompass various scenarios, accounting for the severity and timing of physical risk realizations. The Trucost dataset evaluates physical risks in three future time periods: short-term (2020), medium-term (2030), and long-term(2050). In this robustness test, we constructed factors at different time horizons using the methodology outlined in Section B. Given that the Trucost Climate Change Physical Risk Data is available only after 2019, we conducted the event studies based on the sample period of

2019-2022. The results are consistent across these temporal variations.

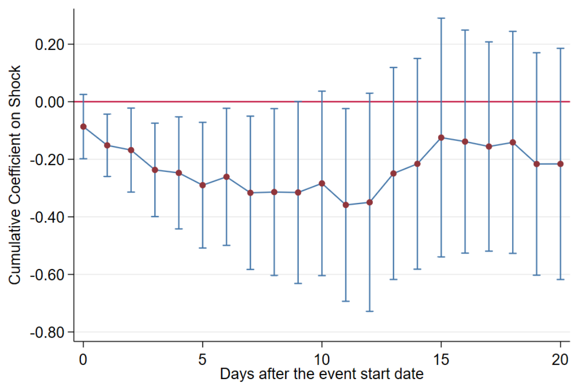
FIGURE A.7: ROBUSTNESS TEST: EVENT STUDY WITH DIFFERENT TIME HORIZONS



(A) SHORT-TERM (2020)



(B) MEDIUM-TERM (2030)



(C) LONG-TERM (2050)

Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + MKT_t + \epsilon_t$. $shock_t$ takes the log value of loss if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. Each physical risk factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval.

D Tail Dependence Estimation

Consider two factors, x and y. Let u be the probability of either stress realizing:

$$P(x < -\theta_x) = P(y < -\theta_y) = u$$

where θ_x and θ_y are the stress levels associated with the two factors. The conditional probability that y is extreme when x is extreme is defined by:

$$P(y < -\theta_y | x < -\theta_x) = \lambda(u)$$

A widely used measure of tail dependence, “coefficient of tail dependenceâ is defined as:

$$\bar{\lambda} = \lim_{u \to 0} \lambda(u)$$

Let α be the probability of *either* stress realizing α:

$$P(x < -\theta_x) \cup P(y < -\theta_y) = 2u - \lambda(u) = \alpha \tag{26}$$

Then the probability of *neither* stress event occurring is $1 - \alpha$.

Suppose that a regulator is interested in finding the maximum expected capital shortfall of an insurer due to both stresses with probability $1 - \alpha$. This problem can be posed as finding the stress levels $(\theta_x, \theta_y) \ni P(x > -\theta_x \cap y > -\theta_y) = 1 - \alpha$ for a prespecified α so that for all $\{x > -\theta_x\}$ and $\{y > -\theta_y\}$, the expected capital shortfall is less than CCRISK.

The solution can be found from equation (26) (Engle, 2023). For the pre-specified level α, we can find u^* that satisfies:

$$u^* = \frac{\alpha}{2 - \lambda(u^*)} \approx \frac{\alpha}{2 - \bar{\lambda}}$$

Similarly, Engle (2023) further shows that the relationship between α and u^* can be extended to three factors:

$$u^* = \frac{\alpha}{3 + \bar{\lambda}_{xyz} - \bar{\lambda}_{xy} - \bar{\lambda}_{xz} - \bar{\lambda}_{yz}}$$

where

$$\bar{\lambda}_{xyz} = \lim_{u \to 0} \frac{P\{(x < q_x) \cap (y < q_y) \cap (z < q_z)\}}{u}$$

Based on the empirical λ estimates visualized in Figure 15, $u^* = 0.01/(3 - 0.035) = 0.0035$.