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

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December 15, 2024

Abstract

We construct a novel physical risk factor using a portfolio of REITs, long on those with properties highly exposed to climate risk and short on those with less exposure. Combined with a transition risk factor, we assess U.S. insurers' climate risk through operations and $13 trillion in asset holdings. Estimating dynamic climate betas, we find higher sensitivity to physical risk among insurers operating in riskier states and to transition risk among those holding more brown assets. Using these betas, we calculate capital shortfalls under climate stress scenarios, offering insights into insurers' resilience to climate risks.

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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 Ralph Koijen, Ana-Maria Tenekedjieva, Kris Jacobs, Shaojun Zhang, Emilia Garcia-Appendini, Katherine Wagner, Celso Brunetti, Simon Rother, Stefano Giglio, Harrison Hong, Caroline Flammer, Wolfram Schlenker, Douglas Almond, Johannes Stroebel, James Stock, Lee Seltzer, Joao Santos, Richard Crump, Nina Boyarchenko, Viral Acharya, Jeffrey Wurgler, 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, Western Economic Association International Conference, WE ARE IN Macroeconomics and Finance Conference, Yale Initiative on Sustainable Finance Symposium, and University of Oklahoma and Review of Financial Studies Climate and Energy Finance Research Conference for their helpful comments.

1 Introduction

Climate change is increasing the frequency and severity of natural disasters, exposing firms to physical climate risks. While measuring this exposure is crucial for risk management and policy decisions, it has proven challenging. Understanding insurance companies' exposure to climate risk is particularly vital, as these institutions serve as the primary risk-sharing mechanism for households and businesses facing natural disasters. This raises a pressing question: can the insurance sector withstand the stress of climate change? The answer has far-reaching implications, given insurers' pivotal role in the financial system, especially as the largest investor group of corporate bonds. Their exposure to climate risk could therefore serve as a key channel through which climate change threatens broader financial stability.

Our study addresses these challenges. First, we develop a novel physical risk factor to capture changes in expected climate risks. This factor leverages a portfolio strategy of Real Estate Investment Trusts (REITs), taking long positions in properties highly exposed to climate risk and short positions in those with lower exposure. Second, we combine this measure with an established transition risk factor following Jung et al. (2025) to assess insurers' climate risk exposure, both through their operations and their $13 trillion financial asset holdings. Importantly, our methodology extends beyond the insurance sector, offering a generalizable framework for measuring climate risk exposure across diverse firms and industries.

Apriori, it is unclear how P&C insurers' operations are affected by physical climate risks. One perspective suggests significant vulnerability: insurers face potential, large losses from extreme weather events and shifting climate patterns, particularly when natural disasters become more frequent and intense than anticipated. This heightened tail risk is especially concerning given documented evidence of insurers' financial constraints (Ge 2022; Ge and Weisbach 2021), as extreme losses can lower insurers' firm value (Froot et al. 1993). However, countervailing forces could potentially buffer insurers against these negative effects. Insurers may adapt by adjusting premiums upward in high-risk regions to reflect increased hazards. Moreover, intensifying natural disasters could drive greater demand for insurance coverage. These two different perspectives underscore the need for a comprehensive empirical measure of insurers' exposure to physical climate risk.

In addition to physical risk affecting P&C insurers' operations, both physical and transition climate risks can affect the $13 trillion of financial asset holdings held by P&C and life insurers. Physical climate events could reduce the value of financial assets. For example, a rise in sea level or hurricanes can cause damage to coastal properties, thereby decreasing the value of mortgage bonds (Nguyen et al., 2022; De Marco and Limodio, 2023). Insurers' assets are also exposed to transition risk, which arises from policy, technology, and preference changes toward less carbon-intensive economies. Insurers heavily invested in fossil fuel companies would likely experience a decrease in asset value as fossil fuel reserves become "stranded" (Litterman et al., 2021).

Measuring insurers' exposure to climate change risks faces multiple challenges. First, data on future climate scenarios and projections are inherently uncertain and rely on various modeling assumptions. While historical data can provide some insights, it fails to address the challenge that perceptions of physical risks can shift without a direct experience of climate change events. Furthermore, climate risks are dynamic, not only because new hazards can emerge or existing ones can intensify, but also because responses from insurers, investors, and households would likely evolve over time. For example, insurers' exposure can change as they adjust their operations, such as deciding where to sell policies.

We use a novel approach to overcome these challenges in assessing insurers' climate risk exposure. Our methodology involves three steps. First, we construct several equity portfolios (factors) that are designed to decline in value as physical risk rises. Second, we estimate insurers' stock return sensitivity (i.e., climate beta) to these physical risk factors from the first step. Third, we use the climate beta estimates to compute the expected capital shortfall of insurers conditional on climate stress. By relying solely on publicly available stock market data, our approach addresses the challenge stemming from the lack of adequate and reliable data. Additionally, we address the second challenge by inferring market perceptions of future climate risk from asset prices. By estimating climate beta dynamically, we circumvent the need to assume static operational portfolios for insurers.

In the first step, we construct several physical risk factors, with our primary factor derived from returns on publicly traded real estate investment trusts (REITs). By observing the locations of properties held by each REIT, we measure REIT-level physical risk exposure by merging location data with county-specific climate risk measures. We then form a portfolio with a long position in the riskiest REITs and a short position in the safest REITs.

The ideal physical risk factor should move with changes in expected physical climate risks, which are difficult to measure. One main way for physical climate risk to manifest itself is through intensified disasters. When disasters are expected to be more severe and frequent, the factor should go down in value. In other words, the factor should be negatively exposed to disasters. Therefore, a feasible validation exercise is to test whether our factor falls when climate-related natural disasters occur. Our event study analyses confirm the factor's desired sensitivity to climate risk: REITs with more exposure to counties with high physical risk, on average, experience a relative 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.

Having established the validity of the factor, we estimate P&C insurers' stock return sensitivity to our physical risk factor, 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 allows for volatilities and correlations to be time-varying. The estimated physical climate betas are positive, suggesting that insurers on average suffer when climate risk increases. These betas change over time and co-move with insurers' disaster losses and attention to climate change. Specifically, the average physical climate beta shows a strong correlation with insurers' losses from homeowners' insurance (0.43) and the first principal component of news-based climate risk indices (0.58).

To better understand variations in climate beta estimates, we examine insurers' portfolios of insurance policies. We hypothesize that insurers that sold more policies in riskier regions tend to exhibit higher physical climate betas. To construct the underwriting portfolio riskiness, we use two ingredients: (1) the geographic distributions of insurers' direct premiums earned across states and (2) the physical risk level of each state, measured by the state's municipal bonds' exposure to our physical climate factor. 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 obtain each insurer's weighted average of state-level physical beta, referred to as *Policy Portfolio Physical Climate Beta*, where the weights correspond to the share of premiums from each state. Our findings show that this beta is significantly and positively correlated with insurers' market-based physical climate beta, supporting the notion that our market-based physical climate beta estimates effectively capture insurers' exposure to physical risk.

Using the estimated physical climate betas, we calculate insurers' expected capital shortfall in a climate stress scenario, termed *CRISK*, following the framework in Jung et al. (2025) and Brownlees and Engle (2017). 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 combining expected equity losses from beta estimates with balance sheet data, such as size and leverage, we estimate the capital shortfall needed to meet prudential requirements. To isolate the effect of physical climate stress from concurrent capitalization, we calculate marginal CRISK, represnting the *addtional* capital shortfall conditional on the climate stress. We find that the aggregate mCRISK has been rising over time, peaking at $10 billion in 2021. This corresponds to 3.3% of aggregate market cap and 7% of NAIC-reported assets.

To measure insurers' exposure to transition climate risk, we follow Jung et al. (2025) and use a stranded asset portfolio that takes a long position in fossil fuel assets and a short position in market. We measure insurers' stock return sensitivity to the transition risk factor, the *transition climate risk beta*. We do this exercise for life insurers as they have a much larger portfolio of financial assets (\$9.9 trillion) than P&C insurers (\$3.3 trillion). The estimated climate betas show a notable increase during the 2019-2020 collapse of fossil fuel prices amid a substantial rise in the attention to climate risk as well as the number of climate-related regulations (Jung et al., 2025; Jung and Hannaoui, 2024).

To further examine the variations in life insurers' transition climate beta, we use detailed insurer asset holding data. We focus on corporate bond holdings, which account for an average of 34% of life insurers' invested assets, making it their largest investment category (Ge and Weisbach 2021). By linking corporate bonds to their respective industries using CUSIP and NAICS, we identify bonds exposed to transition risk. To measure industry exposure to transition risk, we measure each industry's stock return sensitivity to transition climate risk. Based on this approach, we document that insurers with a higher proportion of corporate bond investments in industries facing greater transition risks exhibit larger market-based transition climate betas. This correlation is statistically significant, offering validation to our measure of insurers' transition beta.

The estimated transition marginal CRISKs of life insurers are significant. Using the CRISK framework, we compute and aggregate the marginal transition CRISK for each life insurer. The aggregate marginal CRISK of life insurers rose sharply in 2020 and 2021, driven by the increase in climate beta, peaking at \$70 billion—equivalent to 27% of their aggregate market capitalization. Notably, marginal transition CRISK is concentrated among large life insurers.

In the final part of the analyses, we 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 can assess insurers' resilience when multiple risks 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, estimating the impact of potential comovements of risks in extreme scenarios.

Our analysis shows that the aggregate marginal CCRISK of all U.S. insurers rose in 2020, peaking at $380 billion and remaining relatively high through 2022.[1] This value represents the *extra* capital shortfall associated with a 1% probability compound tail event involving triple stress. Of the $380 billion total, the aggregate marginal compound CRISK for P&C insurers was $140 billion, or 51% of their market cap, while for life insurers, it was $240 billion, representing 66% of their market cap. Overall, these findings suggest that the economic impact of compound climate risk on the insurance sector could be substantial.

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. (2025) 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.[2] In particular, a few studies document that the residential

[1] For context, aggregate systemic risk (SRISK), which represents the marginal expected capital shortfall conditional on market stress, of U.S. financial sector increased by $460 billion during the global financial crisis of 2007-2008.

[2] 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

real estate market prices physical climate risks (Bernstein et al., 2019; Baldauf et al., 2020; Giglio et al., 2021a; Ge et al., 2022).

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-Pinkham et al., 2022; Painter, 2020; Auh et al., 2022; Liu et al., 2021), real estate (Giglio et al., 2021b; Bernstein et al., 2019; Baldauf et al., 2020; Ge et al., 2022), and REIT (Rehse et al., 2019; Feng et al., 2022; Salisu et al., 2024).[3] 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. (2025), 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 applied to all public firms beyond the insurance sector. Second, we focus on insurers, recognizing the critical importance of analyzing their physical risk exposure to comprehensively assess their climate risk exposure. Unlike banks, P&C insurers' liabilities predominantly stem from policyholder claims and obligations which can be directly

equity risk premium. 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. 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, 2024) and bond market (e.g., Hong et al., 2023).

[3] 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.

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 adversely impact expected profits (Alekseev et al., 2022; Grimaldi et al., 2020).

However, other studies find that disasters and climate risk impose negative effects on insurers. 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) find 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 face regulatory frictions in setting rates that adequately reflect rising risks. Massa and Zhang (2021) document that property and reinsurance companies react to Hurricane Katrina by liquidating some of their corporate bond holdings at fire-sale prices. 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. In addition, Wagner (2022), Sastry et al. (2024), and Ge et al. (2024) find that households reduce insurance coverage when faced with rising insurance premiums, suggesting that insurers' total profits can decline even if they can fully price in disaster/climate risk in their policies.

Some insurers may not be adversely affected by rising climate risk, e.g., because they are less financially constrained or they focus on business lines with less regulatory frictions (such as commercial lines). Some insurers may be more adversely affected, as argued by a leading insurance rating agency, AM Best.

> "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]

The arguments on both sides highlight the need to comprehensively assess each insurer's climate risk exposure. By relying on a stock market-based approach, we essentially consider the total effect of climate risk on each insurer. Indeed, our results suggest that some insurers often have negative physical climate exposure, meaning that their stock returns increase when the expected climate risks rise, although on average insurers have positive exposure to physical risk.

Our paper also contributes to the literature on insurers and their risks. A concurrent paper by Powell et al. (2022) studies insurers' resilience to climate risk using insurers' past financial data. In addition, Acharya and Richardson (2014) investigate whether insurers may be a source for systemic risk. Koijen and Yogo (2021) uncover insurers' interest rate and equity market risk exposure through their variable annuity business. Koijen et al. (2024) study aggregate lapsation risk in the life insurance sector. By studying insurers' exposure to climate risk using a market-based approach, we complement the other studies in understanding risks faced by the insurance sector.

Outline of the Paper The remainder of the paper proceeds as follows: Section 2 describes the data. Section 3 develops physical climate risk factors. Section 4 analyzes P&C insurers' exposure to physical climate risk. Section 5 examines the impact of natural disasters on insurer loss, profit, rating, and stock performance. Section 6 studies life insurers' exposure to transition climate risk. Section 7 analyzes compound risk, and Section 8 concludes.

2 Data

2.1 Data Sources

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.[4] Our sample period covers 2000 to 2023.

Our analysis uses these key data sources: (i) REIT property holdings data to construct physical risk factors; (ii) natural disaster event data to capture climate-related physical risk; (iii) stock and corporate bond data to construct market-based climate risk factors; and (iv) insurers' asset holdings and operational exposure data to investigate the relationship between climate risk and insurers' assets and liabilities.

Real Estate Investment Trust Property Holdings Data. We obtain data on the property holdings of real estate investment trust (REIT) from S&P Capital IQ. The data set provides details about the properties' location and characteristics, including their size and value at annual frequency. Covering the years 2010 to 2022, the data set encompasses more than 88,000 distinct properties. We use all publicly traded REITs for which property locations are disclosed. This covers 86% of all US REIT stocks, identified by CRSP share code 18, excluding those identified as financial institutions.[5] We combine this data with FEMA's county-level risk score (or expected losses) to measure REIT-level risk exposure and with CRSP to construct physical risk factors.

[4] 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.

[5] Banks (GICs 4010, diversified financials (GICS 4020), and insurance (GICS 4030).

Natural Disaster Related Data. We use two types of natural disaster-related data: ex-ante disaster risk metrics and ex-post realized disaster events. The former is used for constructing physical climate risk factors, while the latter validates these factors in event studies.

We use the National Risk Index (NRI) from Federal Emergency Management Agency (FEMA) to measure county-level climate risk across the United States. The NRI aggregates data on 18 different hazard types, including hurricanes, wildfires, floods, and droughts, to generate a composite risk score for each county. These scores reflect not only the frequency and magnitude of hazards but also the county's exposure, vulnerability, and resilience to such events. We use the 2023 version of the NRI, which provides a single snapshot of risk levels at the county level, as historical data is not available. This dataset is merged with the REIT property location data to construct physical climate risk factors. Panel A of Figure 1 illustrates the county-level distribution of FEMA scores, indicating that coastal regions in the Southeast and wildfire-prone areas in the West exhibit the highest physical risk.

To validate our physical risk factors, we employ the Billion-Dollar Weather and Climate Disasters Database maintained by National Oceanic and Atmospheric Administration (NOAA), which tracks *daily* weather and climate events causing at least one billion dollars in damage from 1980 to 2023. These events include various types of hazard, such as hurricanes, floods, and wildfires. The database provides event start and end dates, and CPI-adjusted costs, allowing us to identify the timing and impact of major natural disasters in event studies. 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. For analyses requiring county-level damage data over time, we use the Spatial Hazard Events and Losses Database for the United States (SHELDUS), as the NOAA data lack location-specific information.

Stock, Municipal Bond and Corporate Bond Data. In the construction of physical risk factors, we use REIT 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 Municipal Securities Rulemaking Board's (MSRB's) municipal bond transaction database.[6] These bond data are used for validation of climate beta estimates.

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[7] from the National Association of Insurance Commissioners (NAIC) and SNL Financial.[8] 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.

2.2 Insurer Sample Characterization

Our main analysis focuses on listed insurance companies to understand their climate risk exposure. Table 1 presents the summary statistics of the key characteristics of insurers and Table A.1 presents the insurer-level characteristics of the top ten P&C insurers and life insurers based on their average market capitalization from 2000 to 2021.[9] We also analyze nonlisted insurance companies in Appendix B.

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

[7]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.)

[8]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.

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

2.2.1 P&C Insurers

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 can dampen the effect of its total exposure to the risky states. To gauge the degree of each insurer's operational portfolio diversification across states, we compute Herfindahl-Hirschman Index (HHI):

$$\text{Portfolio Concentration}_{i,t} = \sum_{s \in S} \text{Premium Exposure}^2_{i,s,t} \tag{1}$$

where Premium $\text{Exposure}_{i,s,t}$ is insurer i's share of premium earned in state s in year t. A higher value indicates a lower level of diversification, implying that the insurer predominantly sells policies in a small number of states. A value of 1 indicates that the insurer sold 100% of its policies in a single state. The average portfolio concentration by state is 7%, while the range is between 4% and 15%.

We also examine the reinsurance intensity, defined as the proportion of reinsurance ceded to non-affiliated insurers or reinsurers relative to direct premiums. We use reinsurance intensity in the home and commercial multiple peril lines. The reinsurance intensity varies substantially, ranging from less than 1% to 21%. We exploit these cross-insurer variations in operational footprint and characteristics, including reinsurance intensity, in validating our climate beta estimates.

2.2.2 Life Insurers

Life insurers hold large corporate bond portfolio on their asset side. To assess life insurers' corporate bond portfolio exposure to transition risk, we compute a *brown share*, defined as the fair value of brown corporate bonds divided by the fair value of all corporate bonds held by the insurer. While there can be many ways to define brown industries, we use, as a first approximation, the top four industries expected to be most adversely affected by carbon taxes, based on the general equilibrium model of Jorgenson et al. (2018): coal mining, gas mining, gas utilities, and electric utilities.[10] Then, 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.

Panel B of Table A.1 presents the brown share measure. We find that the average brown share is 14.7%, indicating that life insurers' corporate bond portfolio can be substantially exposed to transition risk. We exploit the cross-sectional variation in the compositions of the insurers' corporate bond portfolios to validate transition climate beta estimates. This analysis does not depend on the definition of brown industries but considers all industries using industry-level climate beta estimates.

3 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 from Jung et al. (2025).

3.1 Physical Climate Risk Factors

Our first proposed factor is constructed using returns on real estate investment trusts (REIT). Real estate has a long asset life, making it uniquely exposed to long-term climate risk. A few studies have found that real estate prices are sensitive to long-term climate risk (Bernstein et al., 2019; Giglio et al., 2021b; Baldauf et al., 2020; Keys and Mulder, 2020; Ge et al., 2022). Most publicly-traded REITs in the US disclose their property portfolios, allowing investors to observe which REITs have more assets in regions prone to high physical risk. Given the evidence that physical climate risk is priced in real estate, we can infer

[10] Jung et al. (2023) takes these general equilibrium model estimates to assess the transition risk exposure of banks.

investor's expectation on physical risk from REIT returns.

To build the REIT factor, we first merge REIT property locations with FEMA's county-specific physical risk scores and expected annual losses (EAL) to obtain the REIT-level physical risk exposure. While the rank correlation between the FEMA physical risk score and EAL is 1, their distributions differ; the risk score has a long left tail, whereas the EAL has a long right tail. We use EAL for the baseline as its dollar unit is more directly interpretable, and use risk scores to check for robustness. To compute the REIT-level physical risk exposure, we take the simple average EAL of the property locations. For robustness, we also take the weighted average EAL where the weight is either property size or value.

The REIT-level physical risk exposure is subsequently combined with their returns to sort them into quartile portfolios.[11] We construct the REIT factor as the return from holding long positions in the top portfolio (riskiest REITs) and short positions in the bottom portfolio (safest REITs). Within each portfolio, we compute either equal-weighted returns or value-weighted returns. Panel (A) of Figure 2 shows the 6-month return on the resulting value-weighted REIT physical risk factor.

Figure A.1 plots the distribution of REIT-level physical risk exposure over time. In the cross-section, the figure confirms that there is a substantial variation in exposure. A key driver behind the cross-REIT variation in the exposure is the varying degree of diversification across REITs. Figure A.2 plots the histogram of Herfindahl-Hirschman Index (HHI) at the REIT-level computed based on the number of properties in each county, and it suggests that there is a substantial variation. Given that the FEMA risk metrics are constant over time, the time variation in REIT-level physical risk is entirely attributed to changes in the REITs' property portfolio over time. Therefore, the mild decrease in average REIT physical risk exposure over time can be interpreted as REITs tilting their portfolios towards safer areas on average.

[11] We aim to balance having sufficient observations in each portfolio with maintaining a meaningful contrast between the top and bottom portfolios. Using only two bins reduces the distinction between these portfolios due to the skewed distribution (long right tail) of the REIT-level physical risk exposure. Although three and four bins yield similar results, four bins produce sharper responses in the validation exercise.

We construct variations of the main REIT factor to evaluate the robustness of our analysis. We sort REITs into either two or four portfolios, utilize an alternative location-specific risk measure (FEMA risk score rather than EAL), and implement different methods for calculating REIT-level risk exposure (property size-weighted or value-weighted) and portfolio returns (equal-weighted or value-weighted). We find that these variations have little impact on our results in event studies or climate beta estimation.

Unlike conventional climate shocks measured by temperatures or certain specific types of natural disasters, our approach offers distinct advantages. First, our factor is market-based, allowing us to incorporate the expectations of investors and reduce the reliance on uncertain geophysical climate models. Second, our approach can assess the impact of physical climate risks on firms located across the U.S., rather than being limited to specific locations experiencing rising temperatures or disasters. Focusing on specific disasters or geographical areas does 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.

We provide additional market-based physical risk factors based on various approaches in Appendix IA.D. For example, we construct a factor by sorting stocks based on firm-level physical risk score provided by Trucost. Another factor is constructed using data on US P&C insurers' premiums across states. 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 based on data from SHELDUS. In Figure IA.E.1, we show that these factors also respond significantly to large natural disasters, passing the factor validation test.[12] However, the Trucost factor is available only from 2019, and using the P&C insurer factor as the physical climate factor provides only a relative assessment of

[12]See Figure IA.E.1.

risk exposure among insurers, as the climate beta averages to one by construction. While these factors are useful for other purposes, such as assessing the physical risk exposure of non-insurer sectors, we focus on the REIT factor to measure insurers' physical risk exposure.

Physical Climate Factor Responses around Natural Disasters If the REIT factor captures physical climate risk, we expect the factor to decrease in value after disasters. To test this hypothesis, we conduct event study analyses using natural disaster events that caused more than $1 billion damages. We use the following specification to test the responses of the physical risk factor to disaster events:

$$PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n \, Shock_{t-n} + b^{MKT} \, MKT_t + \varepsilon_t \tag{2}$$

where physical climate factor (PCF) denotes the REIT factor, $Shock_t$ takes the value of damage 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 the REITs with larger weights in our factor, i.e., those with larger exposure to high-risk counties. The standard errors are adjusted using the Newey-West method to account for serial correlation.

Figure 3 shows the cumulative γ coefficient along with a 95% confidence interval. Consistent with the hypothesis, we find that the REIT factor responds significantly negatively to disasters, with larger damages leading to a greater negative effect. To provide some context for the magnitude, multiplying the estimated coefficient of -3% by the mean damage of $7.35 (billion) yields an average response of approximately -22% over 20 days. Given that the factor is standardized to have a mean of zero and a standard deviation of one, this response is not exceptionally large. However, we observe that the response remains statistically significant and persistently negative over the 20-day window.

3.2 Transition Climate Factor

Following Jung et al. (2025), 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. (2025) document that this factor tends to fall following climate policy-related events.

Panel (B) of Figure 2 shows the 6-month cumulative returns of the market portfolio (SPY), transition risk factor (stranded asset factor), and physical risk factor (REIT factor). We report summary statistics and correlations of these factors in Table A.2 and Table A.3.

4 Insurers' Physical Risk Exposure

In this section, we analyze P&C insurers' exposure to physical climate risk. We begin by estimating physical climate beta using the physical climate factor constructed from Section 3.1. Then, we examine the correlation between insurers' physical climate beta and a measure of risk based on their operational portfolios. Lastly, we compute their expected capital shortfall conditional on physical climate stress.

4.1 Physical Climate Beta

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

$$r_{i,t} = \beta_{i,t}^{Mkt} MKT_t + \beta_{i,t}^{Physical} PCF_t + \varepsilon_{i,t} \tag{3}$$

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 physical climate factor (REIT 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 insurer i to overall market risk and physical risk. We call $\beta_{i,t}^{Physical}$ physical climate beta.

We begin by examining the average time-series variation in physical climate beta, shown in Figure 4. The figure shows that physical climate beta changes over time, underscoring the importance of dynamic estimation. In addition, the average climate beta remains positive for most of the sample period, with a notable peak during 2020 and 2021.

We propose two potential drivers of this overall time variation, supported by suggestive evidence. First, we show that the average physical climate beta co-moves with insurers' losses incurred by extreme weather events. An ideal analysis would be to compare the two variables at the insurer-time level; however, insurers typically do not report weather-related losses separately. To address this limitation, we assume that weather-related losses represent a constant proportion of total losses resulting from homeowners' insurance and overlay the average value with the average climate beta in Figure A.8. The correlation between the two is 0.43. Furthermore, for insurers that do report losses from extreme weather events, we anecdotally document a close comovement between physical climate beta and weather-related losses, as illustrated by examples from AllState and Cigna in Internet Appendix Figure IA.A.1. Second, we find suggestive evidence showing that attention to climate change risk plays an important role. To measure the attention to climate change risk, we take the first principal component of six news-based climate change risk indices from climate finance literature.[13] Figure A.9 illustrates the positive comovement between physical climate beta and climate attention, with a correlation of 0.58.

[13]Since these indices are typically quarterly, we correlate them quarterly. See Jung and Hannaoui (2024) for more details.

Figure A.4 plots insurer-level physical climate betas over time, showing a strong co-movement across insurers. Time fixed effects explain 18% of the variation in physical climate betas, while insurer fixed effects explain 5%, indicating that time-varying factors have stronger explanatory power than time-invariant insurer characteristics. As a robustness test, we include three additional factors, interest rate factor, credit risk factor, and REIT market factor, and we find that the physical climate beta variations remain consistent (Figure A.5), mitigating concerns about other confounding factors.

4.2 Insurers' Physical Climate Beta and Their Operational Exposure

To understand both time-series and cross-sectional variation in the physical climate beta, we examine insurers' operational exposure across states. We hypothesize that insurers with more policies in higher-risk states exhibit higher physical climate beta. To test this, we construct a measure of the riskiness of P&C insurers' portfolio of insurance policies, using two ingredients: (1) the geographic distributions of insurers' direct premiums earned across states and (2) the physical risk level of the locations.

We measure the latter using the sensitivity of municipal bond returns to the physical risk factor. Prior studies (e.g. Auh et al., 2022) document that municipal bonds experience negative cumulative abnormal returns following natural disasters. Goldsmith-Pinkham et al. (2022) find that sea level rise exposure risk is priced in municipal bond markets. These findings suggest that physical climate risk is likely priced in the municipal bond market.

4.2.1 A Measure of County Exposure to Physical Climate Risk: Municipal Bond Abnormal Returns

Sample Municipal Bonds. We combine municipal bond transaction data and characteristics data to construct a panel of municipal bond returns. The transaction data, sourced from the Municipal Securities Rulemaking Board (MSRB), include CUSIP, trade date, traded price, and type of transaction. Additional bond information, such as issue amount, CUSIP, and issue ID, is obtained from the Mergent Municipal Bond Database. We merge the MSRB and Mergent datasets by CUSIP to locate each municipal bond. Our final sample includes 150,666 bonds issued by 1,386 counties, with price data covering January 2005 through June 2022. 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.[14]

Municipal Bond Return Estimation. To account for the infrequent trading of municipal bonds, we take the repeat sales model in computing returns, following Auh et al. (2022). The key idea is to compute the average of all municipal bond returns within the same county weighted by issue amount and trading interval. We calculate volume-weighted price averages for all intra-day trades for each day. Then, we use the last available price of the month to obtain monthly prices. (See Appendix IA.C for more details on the implementation of the repeat sales model.)

Using the computed county-month level municipal bond returns, we estimate the physical climate beta for each county at a monthly frequency following the specification in equation (3). Because insurers' operational footprints (e.g., direct premium earned) are comprehensively available only at the state level, we aggregate county-level municipal bond physical climate betas to the state level. For this aggregation, we focus on counties with positive climate betas and use extreme values from each county's distribution to compute state-level climate betas. 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.[15] 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. We focus on the right

[14]We also remove data errors by excluding observations with time to maturity of more than 100 years, coupon rate more than 20%, or a price lower than \$50 or greater than \$150 (on a \$100 notional).

[15]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.

tail of the climate betas for each state, as insurers are likely to face the highest climate risk from municipalities most exposed, while the effects on some municipalities may be muted due to the nature of their cash flows. The results are robust to using the 95th percentile, or maximum value, instead of the 99th percentile.

4.2.2 Insurer Policy Portfolio Climate Beta

Using the state-month municipal bond physical climate beta estimate as a proxy for physical risk exposure of each state, we evaluate the riskiness of each insurer's policy portfolio. This is feasible because we observe each insurer's policy portfolio composition (premiums earned from each state). That is, we consstruct insurer i's policy portfolio physical climate beta at time t as:

$$\text{Policy Portfolio Physical Climate Beta}_{i,t} = \sum_{s \in S} w_{i,s,t}\ \beta_{s,t}^{Physical} \tag{4}$$

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

We test whether market-based physical climate beta (of insurers) capture the riskiness of their policy portfolio using the following OLS specification:

$$\beta_{it}^{Physical} = a + b\ \text{Policy Portfolio Physical Climate Beta}_{it} + \text{Insurer Controls} + \delta_i + \varepsilon_{it} \tag{5}$$

The dependent variable, $\beta_{it}^{Physical}$ is insurer i's time-averaged daily climate physical beta for each year.

Table 2 shows the results. Column (2) includes insurer control variables, size, leverage, reinsurance intensity, and risk based capital ratio. 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. Column (4) adds time-fixed effects. Standard errors are clustered at the insurer level. In all specifications, we find that b is positive and significant. These findings imply that the physical climate beta of insurers reflects the geographical regions in which they operate and the associated physical risk levels of those regions, thereby adding the validity of the climate beta estimates.

4.3 Physical CRISK and Marginal CRISK

Using our physical climate beta measure, 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. Following the framework of Jung et al. (2025), CRISK is defined as the expected capital shortfall conditional on climate stress:

$$\begin{aligned} CRISK_{it} &= E_t[\text{Capital Shortfall}_i \mid \text{Climate Stress}] && (6) \\ &= E_t\left[k(D_{it} + W_{it}) - W_{it} \mid \text{Climate Stress}\right] && (7) \\ &= kD_{it} - (1-k) \underbrace{(1 - LRMES_{it})}_{=\exp\left(\beta_{it}^{Climate} \log(1-\theta)\right)} W_{it} && (8) \end{aligned}$$

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 (6) 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 (8). Climate beta is estimated from equation (3) 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 17% for physical risk, as 17% 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, by construction.

Because CRISK is higher for undercapitalized insurers by construction, we introduce a related measure called marginal CRISK (mCRISK) to isolate and focus on the effect of climate risk. 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:

$$mCRISK_{it} = (1-k) \cdot W_{it} \cdot LRMES_{it} \tag{9}$$

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:

$$LRMES_{it} = -E_t \left[R^i_{t,t+h} | R^{ClimateFactor}_{t+1,t+h} < C^{'} \right] \tag{10}$$

We compute mCRISK for each insurer and aggregate it across all listed P&C insurers to measure their aggregate capital shortfall coming from physical climate risk. We focus on the positive values of marginal CRISK, as one insurer's excess capital would not likely be easily transferrable to reduce another insurer's capital shortfall. Figure 5 plots the aggregate mCRISK by size group[16] and suggests that the aggregate mCRISK is rising over time, peaking at $10 billion in 2021, which corresponds to about 3.3% of their aggregate market cap. A caveat is that this likely underestimates the magnitude, as the average insurer's book assets representing the insurance arm (from NAIC data) account for only 46% of the holding company's total book assets (from Compustat). Thus, when scaled to the size of the P&C insurance operation, the mCRISK value would exceed 7%, based on a back-of-

[16]We define large insurers as the ones with above median assets, and the rest as small insurers.

the-envelope calculation. The notable increase in 2021 is driven by higher climate beta, likely due to the factors suggested in Section 4.1. The aggregate marginal CRISK is more concentrated among large insurers, as the size effect, W dominates the effect of LRMES in equation (9); while small insurers have slightly higher climate beta, large insurers have a much larger market cap. For completeness, we report the non-truncated marginal CRISK values in Figure A.7.

Once we account for the concurrent capitalization of insurers, CRISK, the total expected capital shortfalls conditional on climate stress are mostly negative. Appendix Figure A.10 shows the estimated physical CRISK of the top ten largest U.S. P&C insurers, and the negative values can be interpreted as excess capital reserves. Overall, P&C insurers appear to be well capitalized and therefore even in a 1-percent tail physical climate event, their expected capital shortfall is negative. Nevertheless, mCRISK has been increasing over time, underscoring the importance of continued monitoring despite its current low level of CRISK.

One limitation of our approach is that CRISK can only be computed for listed insurance companies, as it relies on estimating the relationship between a financial firm's stock returns and the climate risk factor. To address this, we sketch an approach in Appendix B to estimate the CRISK of nonlisted insurers by imputing their climate beta using state-level premium data and the coefficients from Table 2. This approach builds on the methods proposed by Engle and Jung (2023) and Engle et al. (2024).

5 Adverse Impacts of Physical Risk on P&C Insurers and P&C Insurer Factor

Our findings on P&C insurers' physical climate betas suggest that their stocks perform worse as physical climate risk increases (i.e., when physical risk factor declines). In this section, we analyze how insurers' operations and stocks perform following natural disasters, which is a form of realization of climate risks.

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.[17] Such exits reduce the total addressable market and potential profits of insurers. Therefore, worse-than-expected natural disasters can cause substantial losses for insurers, leading to a decline in their stock prices.

If insurers can significantly raise premiums or if demand for insurance sharply increases, their stock returns can respond positively to disasters. However, since higher prices tend to reduce insurance demand (Wagner, 2022; Sastry et al., 2024; Ge et al., 2024), the overall effect on profitability is unclear. In addition, climate change intensifies disaster risks, increasing tail risks for insurers' losses. Given evidence of the tightening of insurance financial constraints after losses (Koijen and Yogo, 2015, 2022; Ge, 2022; Ge and Weisbach, 2021; Oh et al., 2022), extreme losses can lower insurers' firm value (Froot et al. 1993). Moreover, climate change also increases insurers' reinsurance costs and modeling uncertainty, as indicated by the quote below from Progressive Insurance Group's 2022 climate disclosure.

> "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]

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

Therefore, we assess how natural disasters, which are realizations of some climate risks, affect P&C insurers' short- and long-term losses, profits, ratings, and stock returns in this section.

5.1 Impact of Physical Risk on P&C Insurer Losses, Profits, and Ratings

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:

$$Y_{i,t} = \beta \text{ Disaster Loss}_{i,t} + \text{Control}_{i,t} + \gamma_t + \delta_i + \epsilon_{i,t} \tag{11}$$

where the independent variable $Y_{i,t}$ is one of the four outcome variables for P&C insurer i in year t: an indicator of rating downgrade, direct losses incurred, short-term profitability, and long-term profitability[18]. Disaster Loss$_{i,t}$ represents the weighted average damages for states, with the weight being the insurer's exposure in that state, calculated as the proportion of premiums earned there. The damage of a state is measured by the property damage based on SHELDUS (in logarithms):

$$\text{Disaster Loss}_{i,t} = \sum_{s \in S} \left[\left(\frac{\text{Premium}_{i,t,s}}{\sum_{s \in S} \text{Premium}_{i,t,s}} \right) \times \text{Log Property Damage}_{t,s} \right] \tag{12}$$

Control variables include reinsurance intensity, log assets, leverage, and risk-based capital ratio. γ_t and δ_i denote year and insurer fixed effects.

Table 3 shows the results on insurers' rating downgrade. The positive and significant coefficients on the disaster loss suggest that following larger disaster damages, P&C insurers are more likely to be downgraded. Table 4 reports the results on the loss and profitability. The findings suggest that following more severe disasters, the direct incurred losses of P&C insurers rise, leading to a decrease in both their short-term and long-term

[18] The four regressions differ in their use of time lags: rating downgrades use one-year lags, loss incurred and short-term profitability use contemporaneous data, and long-term profitability uses a three-year lag.

profitability up to three years after disaster.

The long-term profitability result implies that insurers suffer long-term consequences due to disasters. One reason could be that downgrades cause a demand reduction. Another reason could be that losses tighten financial constraints and reduce the quantity of insurance that insurers are willing to sell (Froot et al., 1993). A third reason is that insurers raise premiums (Oh et al., 2022) and experience demand drops as a result (Wagner, 2022; Sastry et al., 2024; Ge et al., 2024). The demand drop is large enough to drive down profitability despite premium increases. In sum, these results indicate that as climate change exacerbates natural disasters, insurers are likely to experience worse financial performance.

5.2 Impact of Physical Risk on P&C Insurer Stock Return and P&C Insurer Factor

In light of the documented adverse impact of disasters on P&C insurers' ratings, losses, and profits, we propose another climate risk factor derived from the stock returns of P&C insurers and evaluate the validity of the factor by showing that their stock returns are sensitive to physical risk exposure and decline when disasters occur. The objective of this exercise is twofold: first, to document the negative impact of natural disasters on P&C stock returns; and second, to propose another climate risk factor for asset pricing tests or measuring physical risk exposure of non-insurance firms.

We form a portfolio of all listed U.S. P&C insurers where the weight is the $DisasterLoss$ from equation (12) scaled by each insurer's market cap. This approach assigns greater weight to insurers with higher physical risk exposure, proxied by past disaster losses relative to equity. Although past disaster losses may not perfectly capture physical risk exposure, insurers commonly use past damage realizations as a primary input in assessing physical risk. As robustness tests, we replace past log property damage with the standard deviation of past damages and substitute premiums with the net premium (after losses).

The resulting factors remain highly correlated, supporting the robustness of our approach. We subtract the risk-free return from the portfolio return to form a zero-cost portfolio.

Next, we test whether the P&C factor responds to natural disaster events, by regressing the P&C factor on disaster dummies, controlling for market return:

$$P\&C\ Factor_t = \alpha + \sum_{n=0}^{20} \gamma_n\ Shock_{t-n} + b^{MKT}\ MKT_t + \varepsilon_t \tag{13}$$

$Shock_t$ 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. The coefficient γ is expected to be negative if the occurrence of a natural disaster is bad news for insurers with higher weights in the P&C stock portfolio, 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.

Figure 6 shows the cumulative γ coefficient along with the 95% confidence interval and suggests a negative response to the occurrence of natural disasters, consistent with the hypothesis. We note that the response of the P&C insurer factor to disasters is slower than that of the REIT factor, possibly due to differences in information transparency. The impact of disasters on REITs is relatively easier to assess, as property locations are publicly disclosed. In contrast, evaluating the impact on insurance companies is likely more complex. The details of policies sold by insurers are not publicly available, operational footprint information is limited to the state level, and reinsurance contract details are often non-transparent, making it difficult to determine the *net* exposure of specific insurers.

We conduct a series of robustness tests to ensure the reliability of the event study results. First, we find that the portfolios constructed using alternative portfolio weighting exhibit similar responses to natural disaster events (Appendix Figure IA.E.1). Second, results are consistent 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 IA.E.2).

Third, we find that the results remain robust 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 IA.E.3). These results suggest that P&C insurers' stock returns tend to decline following large natural disasters, making P&C factor potentially useful for measuring the physical risk exposure of non-insurance firms. A limitation of using the P&C factor to assess insurers' own physical risk exposure is that the resulting CRISK estimates would be ordinal (i.e., relative among insurers) rather than cardinal, as the weighted average climate beta is mechanically equal to 1.

In sum, this section demonstrates that disasters negatively impact P&C insurers' operational performance and stock returns, supporting the use of the P&C factor as a market-based proxy for physical climate risk.

6 Insurers' Transition Risk Exposure

In this section, we shift our focus to analyze life insurers' exposure to transition risk, positing that their assets— particularly corporate bond holdings— can be vulnerable to transition risk. We focus on life insurers as they have a much larger portfolio of financial assets (\$9.9 trillion) than P&C insurers (\$3.3 trillion). Similar to the Section 4, we first estimate transition climate beta, and we examine the relationship between our transition climate beta with a measure based on life insurers' portfolio of corporate bonds. Lastly, we compute insurers' expected capital shortfall conditional on transition climate stress.

6.1 Transition Climate Beta

We estimate the transition climate beta for life insurers using the following model:

$$r_{i,t} = \beta_{i,t}^{Mkt} MKT_t + \beta_{i,t}^{Transition} TCF_t + \varepsilon_{i,t} \tag{14}$$

where $r_{i,t}$ is the stock return on life insurer i and transition climate factor, TCF_t, is the stranded asset factor developed by Litterman et al. (2021). The intuition behind this factor is that as transition risk increases, demand for fossil fuel reserves is likely to decline ultimately, making the performance of the fossil fuel sector (relative to the market) a proxy for transition risk. Jung et al. (2025) show that this factor tends to fall following “brown" events— events associated with a movement against a greener economy— and it tends to rise following “green" events (e.g., Paris Agreement), in event studies.

Figure 7 displays the transition climate beta of large U.S. life insurers. From 2000 to 2019, the climate beta remains near zero but rises sharply in 2020. Time fixed effects explain a larger proportion of the variation (R-squared of 30%) compared to insurer fixed effects (R-squared of 9%). Notably, insurers' transition climate betas increased significantly during 2019â2020, coinciding with a collapse in fossil fuel prices and heightened attention to climate change risks. This aligns with our finding in Section 2 that the brown proportion of insurers' corporate bond portfolios is significant, averaging 14.7%. While cross-sectional variation in transition climate betas is low until 2019, the magnitude of the 2020 increase varies significantly across insurers. In the next subsection, we explore this variation using data on insurers' asset holdings.

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, to measure the transition risk exposure of bond portfolios, we construct a panel of bond portfolio climate betas. For each insurer, we calculate the weighted average climate beta, where the weights are the proportions of bond holding in the respective industry, and investments are assigned the climate beta of the respective industries:

$$\text{Bond Portfolio Transition Climate Beta}_i = \sum_{j \in J} w_j \; \beta_j^{Transition} \tag{15}$$

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 obtained by regressing each industry return on market factor and the transition climate factor.[19] This approach avoids defining brown industries as a dummy variable, instead using industry climate beta as a continuous measure. Moreover, by dynamically estimating industry climate betas, it addresses the challenge that "brownness" of an industry can change over time.

We compare the insurer transition climate beta estimates with bond portfolio transition climate beta using the following OLS specification:

$$\beta_{it}^{Transition} = a + b \text{ Bond Portfolio Transition Climate Beta}_{it} + \text{Insurer Controls} + \delta_i + \varepsilon_{it} \tag{16}$$

The dependent variable, $\beta_{it}^{Transition}$ is insurer i's time-averaged daily climate transition beta for each year. We use the same insurer control variables as in the previous sections. Standard errors are clustered at the insurer level. 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. 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.

[19] Industry returns are calculated based on the value-weighted returns for each sector, incorporating all publicly traded companies in the United States. For further details, refer to Jung et al. (2025).

6.3 Transition CRISK and marginal CRISK

Using the CRISK framework, we compute the marginal transition CRISK for each life insurer and aggregate them up. Figure 8 shows that the aggregate marginal CRISK of life insurers increased sharply in 2020 and 2021, driven by the rise in climate beta, peaking at $70 billion. This corresponds to 27% of their aggregate market cap. Comparing small and large life insurers, we find that the marginal transition CRISK is concentrated among large life insurers, in contrast to the distribution of marginal physical CRISK shown in Figure 5.

We also examine the transition marginal CRISK at the individual insurer level (Figure A.12). Their time-series variation is similar to those of banks analyzed in Jung et al. (2025). 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%). However, due to size effects, insurers' marginal CRISK values are generally smaller; the maximum for banks is $ 120 billion, while for insurers is less than $15 billion. Once the concurrent capitalization is considered, many large life insurers exhibit negative transition CRISKs (Figure A.11), a contrast to the banking sector, where large banks had significant positive CRISK during 2020-2021.

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 simultaneously, 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. Unlike correlation, which measures linear relationships, tail dependence provides better assessment of joint risk under severe stress, especially when multiple stresses interact non-linearly. For instance, during financial market stress, natural disasters may amplify stress levels in the insurance sector, exceeding the combined effect of each event occurring independently.

Figure 9 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)). Panel (a) uses daily 6-month return data from 2000-2021, while panels (b)-(d) use data from 2011-2021, constrained by the availability of the REIT factor.

Between transition and market risk, we find some tail dependence, as presented in panel (a). As the market stress (or transition stress) gets more extreme (i.e., x-value approaches zero), the probability of both stresses realizing conditional on the single stress (y-value) is 13%. However, we do not find tail dependence between transition risk and physical risk, or between market and physical risk. This may be due to limited sample size; in a longer time series there may be more realizations of simultaneous tail events.[20] Considering these tail dependence, the previous 1-percentile stress quantile is adjusted to 0.35-percentile stress for *each* factor.[21] This corresponds to 39%, 62%, and 18.6% decline in market factor, transition factor, and physical factor, respectively.

[20] See Figure IA.B.1 showing pair-wise joint distributions. Note that there are no observations in the bottom left corner in the joint distributions of transition and physical factors or market and physical factors.

[21] See Appendix IA.B for a detailed description of the estimation methodology.

7.2 Compound CRISK

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

$$r_{it} = \beta_{it}^{Mkt} MKT_t + \beta_{it}^{Trans} TCF_t + \beta_{it}^{Phys} PCF_t + \varepsilon_{it} \tag{17}$$

Then, by using the beta estimates, CCRISK can be computed as:

$$CCRISK_{it} = kD_{it} - (1-k) \cdot W_{it} \cdot (1 - LRMES_{it}) \tag{18}$$

where the long-run marginal expected shortfall is computed based on the three beta estimates:

$$LRMES_{it} = 1 - \exp\left(\beta_{it}^{Mkt} \log(1-\theta^{Mkt}) + \beta_{it}^{Trans} \log(1-\theta^{Trans}) + \beta_{it}^{Phys} \log(1-\theta^{Phys})\right) \tag{19}$$

The tail dependence is captured by using the adjusted stress levels determined from the tail dependence parameter estimates from the previous subsection (i.e., $\theta^{Mkt} = .39, \theta^{Trans} = .62, \theta^{Phys} = .186$).

Analogous to the one-dimensional marginal CRISK, we define marginal compound CRISK as the difference between stressed CRISK and non-stressed CRISK, where the stress is the union of three stress events (market stress, transition stress, and physical stress). We still focus on the 1 percent tail event; that is, the probability of at least one stress event being realized is 1%. Figure 10 shows that the aggregate marginal CCRISK of P&C insurer reached \$140 billion in 2021, which corresponds to 51% of their market cap. This can be interpreted as the additional expected capital shortfall in the scenario of triple stress. The aggregate marginal CCRISK of life insurers peaked at \$240 billion in 2021, which is 66% of their market cap. For completeness, we report Figure A.13 showing the estimated marginal CCRISK for the top 10 P&C insurers and the top 10 life insurers. Combined together, our estimates suggest that the effect of compound risk can be substantial.[22]

8 Conclusion

This paper evaluates insurers' exposure to physical and transition climate risks. We develop a novel physical risk factor by constructing a portfolio of REITs, taking a long position on those with properties more exposed to physical climate risk and short on those less exposed. We validate this factor by confirming its negative response to large natural disasters. Using this factor, we estimate the dynamic climate betas, which capture the stock return sensitivity of each insurer to the physical risk factor.

The estimated physical climate betas vary over time, with the average beta strongly co-moving with insurers' incurred losses, particularly catastrophe losses from extreme weather events. We also suggest the importance of climate change attention, finding a high correlation between a climate attention measure and the average climate beta. In addition, we find that insurers with greater exposure to risky states tend to have higher physical climate betas, indicating that the beta reflects P&C insurers' operational footprint.

Using the climate beta estimates, we compute insurers' CRISK, the expected capital shortfall conditional on climate stress, following the approach of Jung et al. (2025). By construction, insurers with higher leverage have higher CRISK. To isolate the leverage effect and focus on the effect of climate stress, we also compute insurers' marginal CRISK, the difference between CRISK and non-stressed CRISK. We find that the marginal CRISK for listed US P&C insurers has risen over time, peaking at $6 billion in 2021, coinciding with heightened catastrophe losses and climate change attention.

We also examine life insurers' exposure to transition risk. We use the stranded asset portfolio as the transition risk factor and estimate life insurers' transition climate beta. We observe a notable increase in their transition climate beta during the 2019-2020 fossil fuel

[22] However, due to their low leverage (capital to asset ratio lower than 8% threshold we are using), the CCRISKs are mostly negative. See Appendix Figure A.14.

price collapse. Empirical validation of 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 more corporate bonds in transition-risk-impacted industries face greater transition climate risk. The estimated aggregate transition CRISK for life insurers in the U.S. also significantly rose by more than $150 billion, equivalent to 28% of their market cap. Excluding concurrent undercapitalization, the marginal CRISK attributed solely to transition climate stress increased by more than $85 billion during the same period.

Finally, we compute compound risk incorporating potential tail dependence among market risk, transition risk, and physical risk. We find that the aggregate marginal compound risk has increased, peaking at $380 billion in 2021, and remained relatively high. Overall, our results suggest that climate risk can have an economically substantial impact on the insurance sector. 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: INSURER SUMMARY STATISTICS

Panel A: P&C Insurer	count	mean	sd	p25	median	p75
Mktcap (Million USD)	269	10.1239	11.4804	3.0334	5.7539	12.6394
Asset (Million USD)	272	38.9925	49.2385	12.6572	23.4862	43.6703
Equity (Million USD)	272	7.3891	6.7931	2.7041	5.0085	9.0921
Reinsurance Intensity (%)	188	7.6025	11.3676	0.0507	1.5493	12.9530
RBC ratio	199	22.2361	34.9039	9.7198	12.1770	18.3883
Leverage	220	0.5413	0.1678	0.5140	0.5866	0.6615

Panel B: Life Insurer	count	mean	sd	p25	median	p75
Mktcap (Million USD)	383	20.7701	28.1045	5.1510	12.1301	26.2532
Asset (Million USD)	385	201.0334	229.8982	34.9665	116.3544	241.5602
Equity (Million USD)	385	18.2875	21.4137	5.0604	10.7638	19.6467
Reinsurance Intensity (%)	227	18.2639	30.7368	1.4582	6.1060	22.4524
RBC ratio	306	9.4871	4.0151	6.9155	8.2479	10.5823
Leverage	306	0.8206	0.1156	0.7927	0.8555	0.8907

Notes: This table provides summary statistics of publicly listed U.S. insurers. Panel A covers 21 Property & Casualty insurers (2011-2021), and Panel B covers 18 life insurers (2000-2020). Reinsurance intensity, Risk-based capital (RBC) ratio, and leverage are asset-weighted averages, winsorized at the 5% level.

TABLE 2: P&C INSURER CLIMATE BETA AND POLICY PORTFOLIO CLIMATE BETA

	Physical Climate Beta			
	(1)	(2)	(3)	(4)
Policy Portfolio Climate Beta	1.537**	2.123***	2.135**	7.820***
	(2.33)	(2.96)	(2.36)	(4.11)
Size		-0.015***	0.033	0.022
		(-3.43)	(0.86)	(0.97)
Leverage		0.053	0.290	0.300
		(0.83)	(1.18)	(1.40)
Reinsurance Intensity		-0.002	-0.033	-0.073
		(-0.04)	(-0.52)	(-0.89)
RBC ratio		0.000	0.000	-0.000
		(1.07)	(0.35)	(-0.26)
Constant	-0.002	0.201**	-0.719	-0.652
	(-0.14)	(2.77)	(-1.12)	(-1.60)
Insurer Controls	No	Yes	Yes	Yes
Insurer FE	No	No	Yes	Yes
Year FE	No	No	No	Yes
N	206	188	187	187

Notes: This table shows results from Equation 5. t-statistics are in parentheses. Standard errors are clustered at the insurer level. The sample comprises all P&C insurers in the U.S., and the annual data spans from 2011 to 2022. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

TABLE 3: P&C INSURERS' RATINGS AND WEATHER LOSSES

	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 disaster loss estimated in Equation 11. Disaster 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). Disaster $\text{Loss}_{t,i} = \sum_{s\in S}\left[\left(\frac{DPE_{i,t,s}}{\sum_{s\in S} DPE_{i,t,s}}\right) * \text{Property Damage}_{t,s}\right]$. 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 4: 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 11. 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 5: LIFE INSURER CLIMATE BETA AND BOND PORTFOLIO CLIMATE BETA

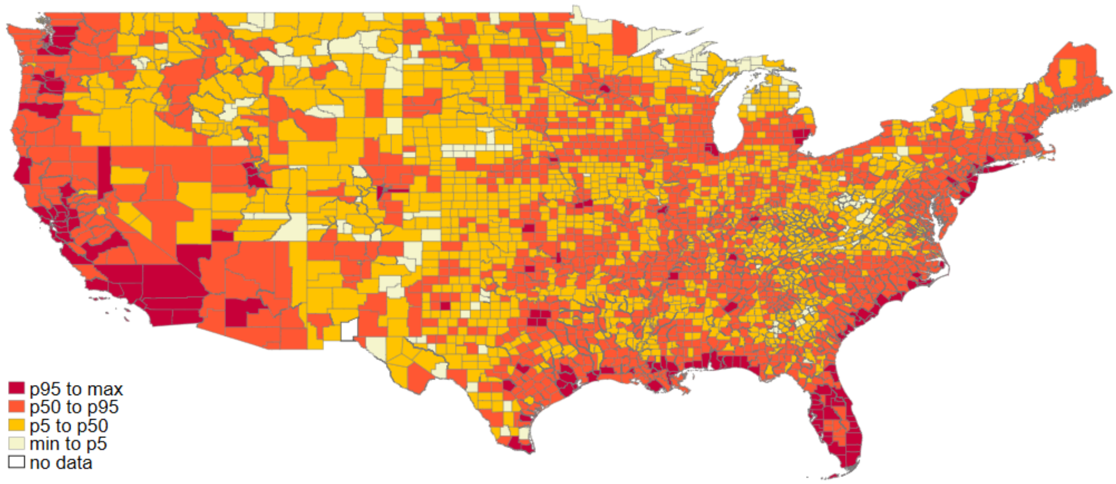
	Transition Climate Beta		
	(1)	(2)	(3)
Holding Portfolio Climate Beta	0.950***	1.389***	1.609***
	(3.48)	(4.57)	(5.66)
Size		0.007	0.000
		(1.02)	(0.01)
Leverage		-0.018	-0.181**
		(-0.14)	(-2.23)
Reinsurance Intensity		0.012	-0.053
		(0.28)	(-1.09)
RBC ratio		0.003	0.006
		(0.77)	(0.99)
Constant	-0.030	-0.209	0.024
	(-1.00)	(-1.34)	(0.14)
Insurer Controls	No	Yes	Yes
Insurer FE	No	No	Yes
N	293	227	227

Notes: This table shows results from Equation 16. t-statistics are in parentheses. Standard errors are clustered at the insurer level. The sample comprises all life insurers in the U.S., and the annual data spans from 2001 to 2022. Significance levels: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

Figures

FIGURE 1: NATURAL DISASTER DATA DESCRIPTIVE STATISTICS

(A) FEMA RISK SCORE



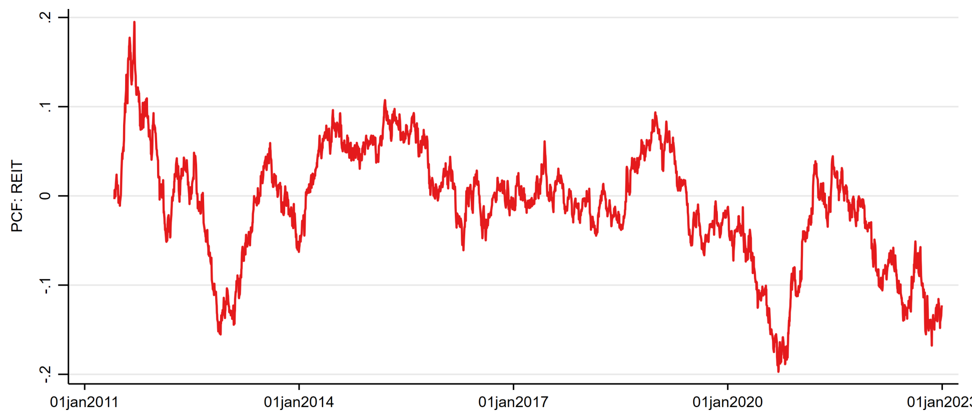
(B) BILLION DOLLAR LOSS

Harzard	Duration (Days)	Mean Loss (Billions $)	Max Loss(Billions $)	Deaths
Hurricane	4	29	190	156
Drought	289	10	39	46
Wildfire	181	7	28	23
Winter	5	4	26	32
Flooding	21	4	14	13
Severe Storm	3	2	13	10

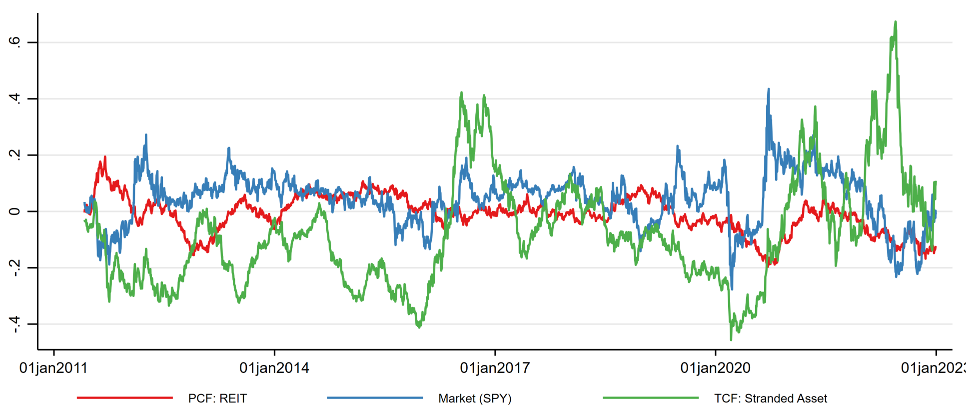
Note: The map shows the county distribution of FEMA scores. The table shows the summary statistics of Billion Dollar Natural Disasters. Loss is the average total loss across events. The sample period is 2000-2022.

Figure 2: 6-Month Returns

(a) Physical Risk Factor

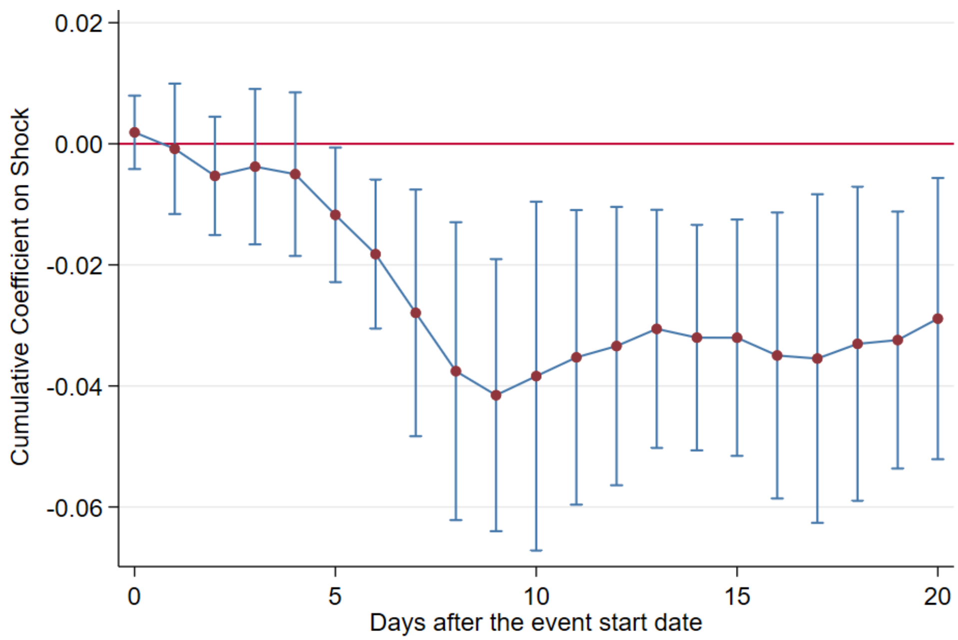


(b) Market, Transition, and Physical Factors



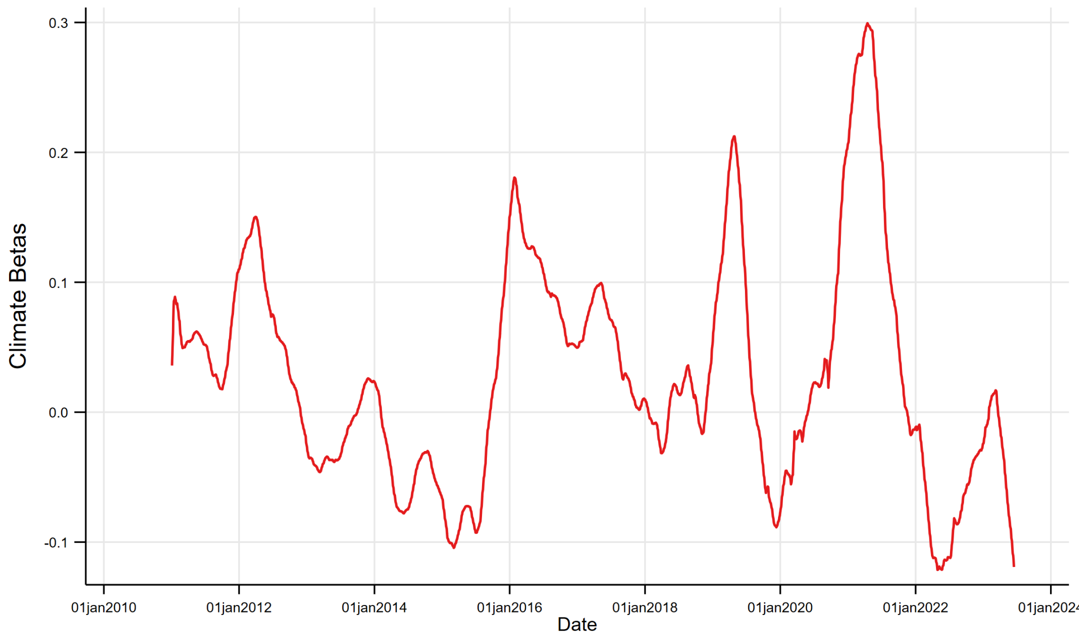
Note: Panel A shows the 6-month cumulative returns of REIT factor. Panel B shows the 6-month returns of the market portfolio (SPY), transition risk factor (stranded asset factor), and physical risk factor (REIT factor).

FIGURE 3: REIT FACTOR RESPONSES AROUND NATURAL DISASTER EVENTS



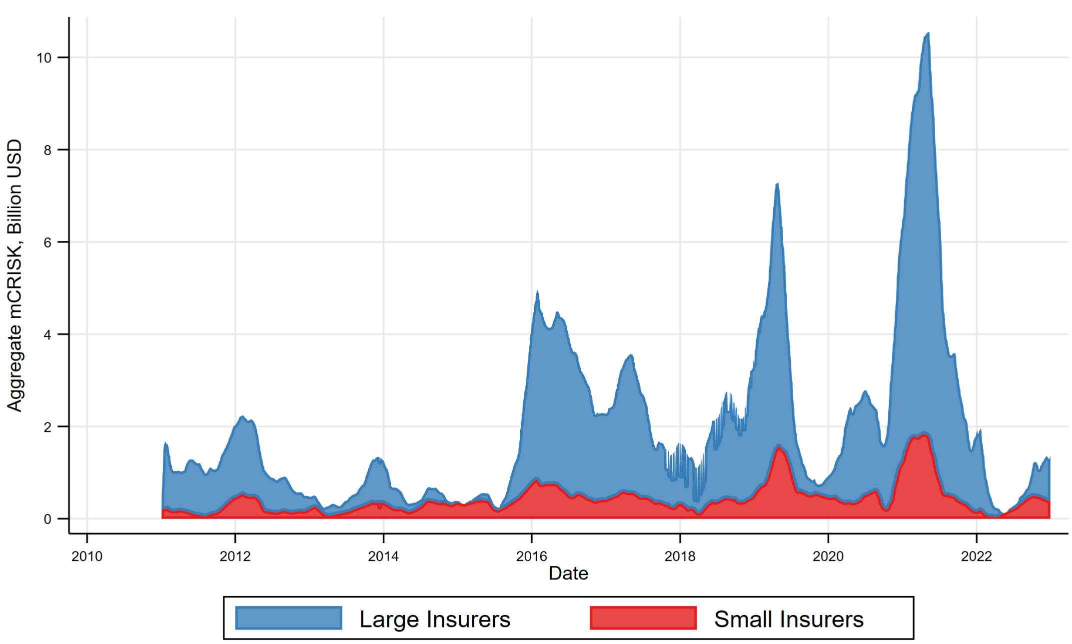
Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + \theta MKT_t + \epsilon_t$. $shock_t$ takes the value of damage if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. In the sample period spanning from 2011 to 2022, a total of 148 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.

FIGURE 4: PHYSICAL CLIMATE BETA OF P&C INSURERS IN THE U.S.



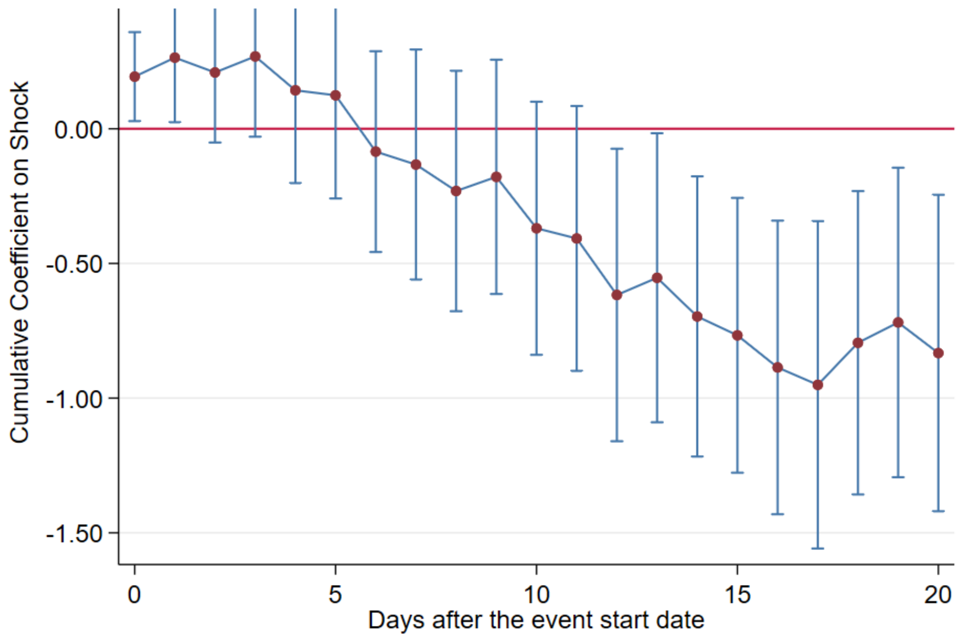
Note: Average Climate beta of P&C insurers in the U.S.. The sample period is from January 2011 to December 2022.

FIGURE 5: AGGREGATE PHYSICAL MARGINAL CRISK OF P&C INSURERS IN THE U.S.



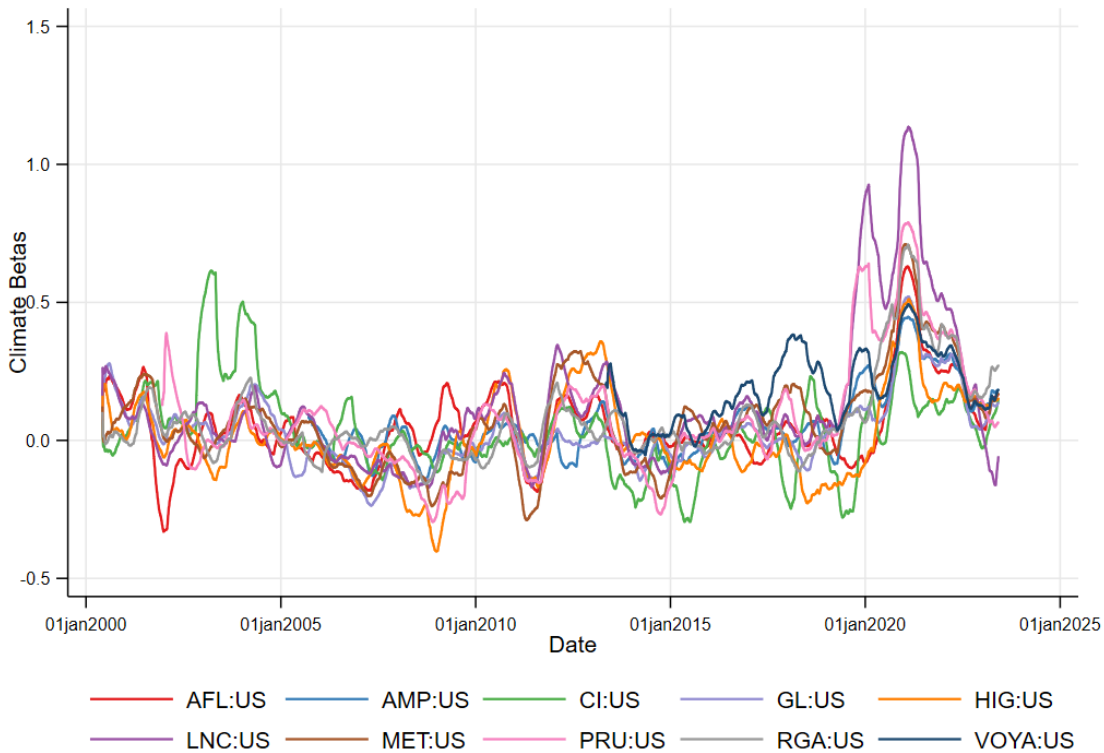
Note: Aggregate physical marginal CRISK of P&C insurers in the U.S.. The large insurers are the top large P&C insurers in Table A.1. The sample period is from January 2011 to December 2022.

FIGURE 6: P&C INSURER STOCKS RESPONSE AROUND NATURAL DISASTER EVENTS



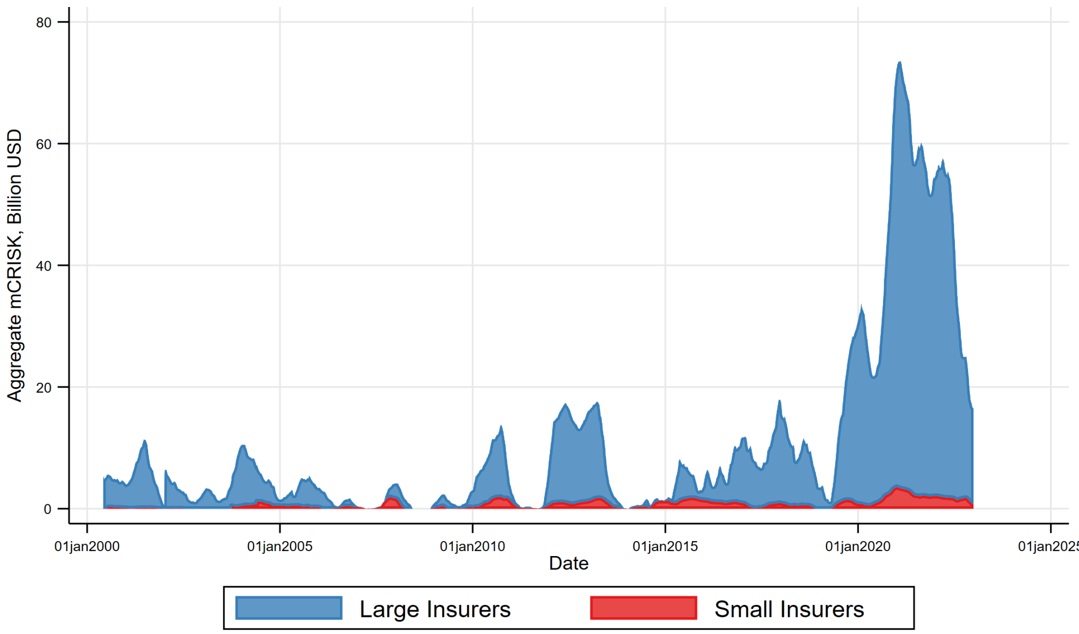
Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + \theta MKT_t + \epsilon_t$. $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. In the sample period spanning from 2001 to 2022. Each physical risk factor series is standardized by its volatility. The standard errors are Newey-West adjusted and the band shows 95% confidence interval.

FIGURE 7: TRANSITION CLIMATE BETA OF LIFE INSURERS IN THE U.S.



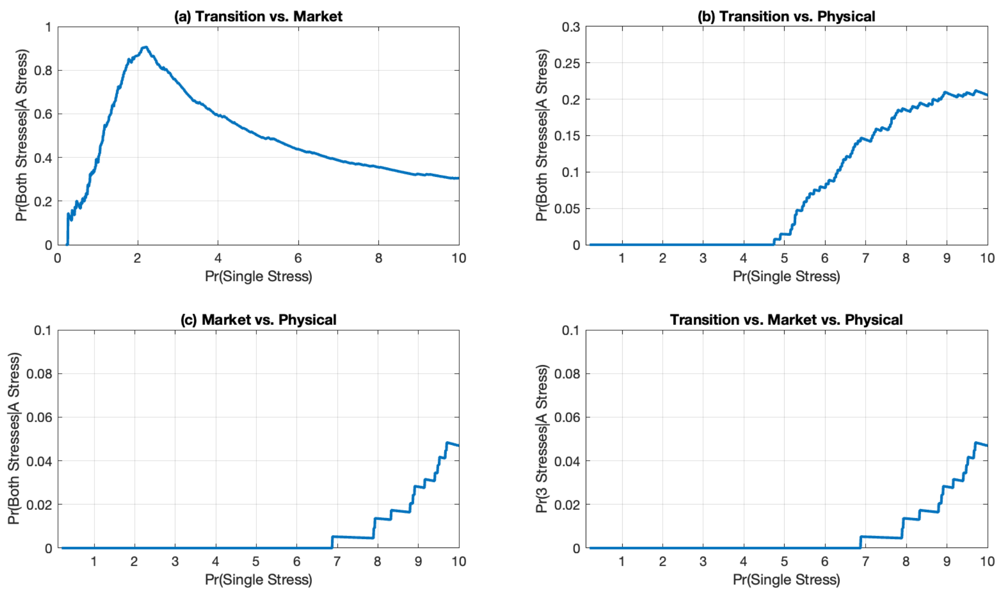
Note: Climate beta of life insurers in the U.S.. The sample insurers are the top large life insurers in Table A.1. The sample period is from June 2000 to December 2021.

FIGURE 8: AGGREGATE TRANSITION MARGINAL CRISK OF LIFE INSURERS IN THE U.S.



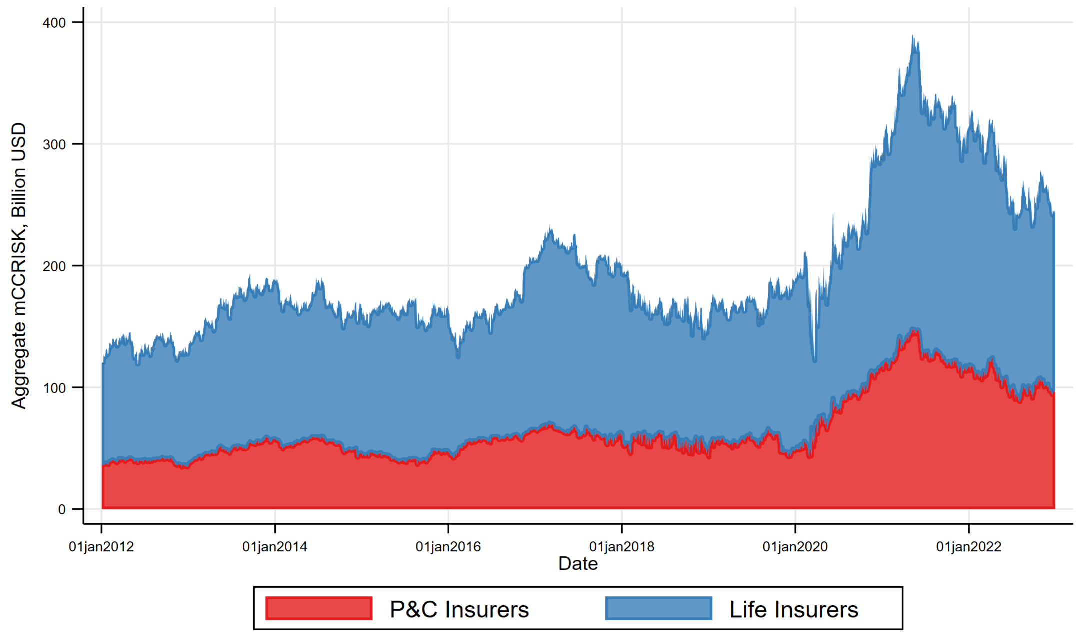
Note: Aggregate transition marginal CRISK of Life insurers in the U.S.. The large insurers are the top large Life insurers in Table A.1. The sample period is from January 2001 to December 2022.

FIGURE 9: 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. Panel (a) is based on the 6-month returns on the factors during 2001-2021; panels (b)-(d) are based on 2011-2021.

FIGURE 10: AGGREGATE MARGINAL COMPOUND TRANSITION AND PHYSICAL CRISK



Note: Aggregate marginal compound CRISK of P&C insurers and life insurers in the U.S.. The sample period is from January 2012 to October 2022.

A Additional Tables and Figures

TABLE A.1: TOP 10 INSURER SUMMARY STATISTICS

Panel A: P&C Insurers Summary Statistics

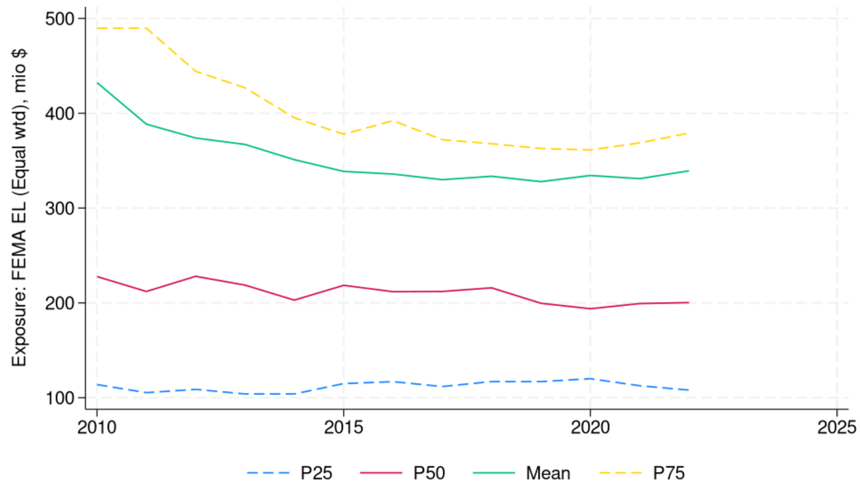
Ticker	Insurer	Mktcap	Asset	Equity	HHI (%)	Reinsurance Intensity(%)
ALL	Allstate	10.17	11.74	9.93	6.61	4.40
TRV	Travelers	10.10	11.41	9.89	4.94	3.48
PGR	Progressive	9.79	10.10	8.81	14.62	0.19
HIG	Hartford	9.64	12.22	9.63	5.12	17.24
CNA	CNA Financial	9.03	10.99	9.29	4.92	20.71
CINF	Cincinnati	8.96	9.77	8.76	7.73	5.27
MKL	Markel	8.59	9.61	8.20	4.94	14.23
AIZ	Assurant	8.52	10.31	8.43	5.33	21.21
WRB	WR Berkley	8.52	9.69	8.11	4.39	3.22
ORI	Old Republic	8.31	9.56	8.31	10.91	10.17

Panel B: Life Insurers Summary Statistics

Ticker	Insurer	Mktcap	Asset	Equity	Corporate Bond	Brown Share(%)
MET	MetLife	10.52	13.25	10.61	10.52	17.20
PRU	Prudential	10.32	13.26	10.40	10.40	13.72
AFL	Aflac	10.08	11.37	9.38	9.24	11.83
CI	Cigna	9.86	11.11	9.09	8.01	13.99
HIG	Hartford	9.64	12.24	9.63	8.90	11.86
AMP	Ameriprise	9.62	11.78	8.96	9.29	18.34
LNC	Lincoln National	9.19	12.14	9.30	10.36	15.59
VOYA	Voya Financial	8.95	12.19	9.39	9.95	12.56
GL	Globe Life	8.70	9.76	8.28	8.73	19.46
RGA	Reinsurance	8.30	10.20	8.29	8.96	12.74

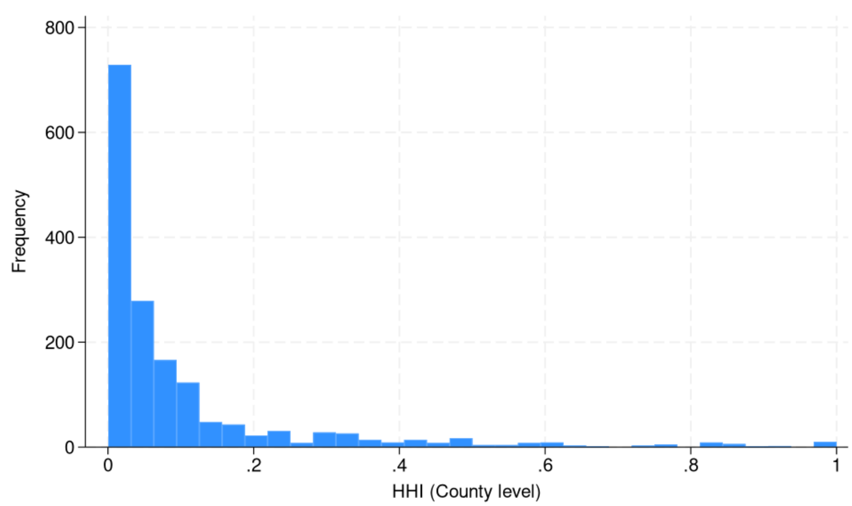
Note: Panel A shows the summary statistics of P&C insurers. HHI (Risky State Exposure) measures the degree of each insurer's operational portfolio diversification averaged across 2000-2021. Reinsurance Intensity is the 95% winsorized, asset-weighted average of individual insurers within the group. Panel B shows the summary statistics of life/health insurers from 2000 to 2021. 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. *Market cap*, *Asset Equity*, and *Corporate Bond* are in log.

FIGURE A.1: REIT-LEVEL PHYSICAL RISK EXPOSURE DISTRIBUTION OVER TIME



Note: Mean, median, 25th percentile, and 75th percentile of physical risk exposure distribution over time.

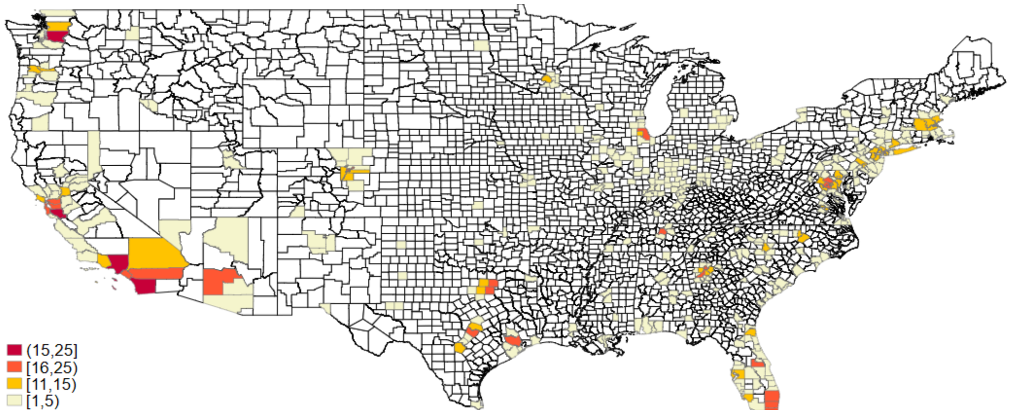
FIGURE A.2: PROPERTY LOCATION DIVERSIFICATION ACROSS REITS



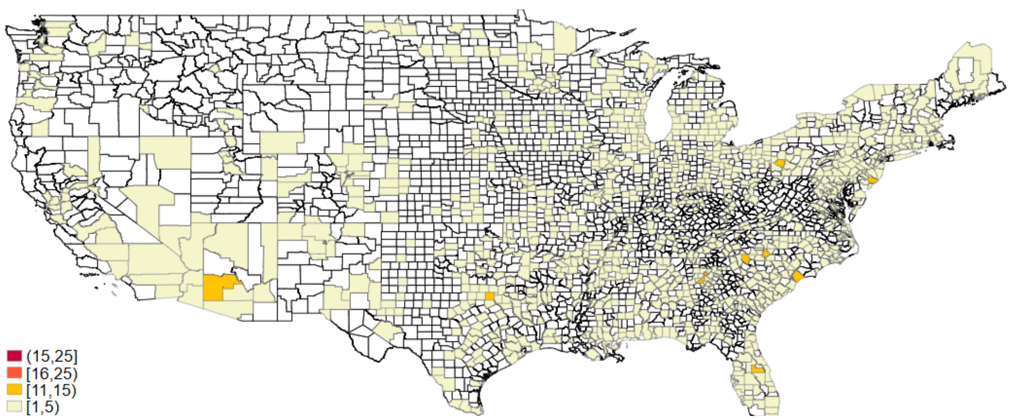
Note: Histogram of Herfindahl-Hirschman Index (HHI) computed based on the share of properties located in each county. (i.e., $HHI_i = \sum(PS_{i,c})^2$ where $PS_{i,c}$ represents the number of properties in county c divided by the total number of properties owned by the REIT i.)

FIGURE A.3: COUNTY DISTRIBUTION OF REITS

(A) RISKIEST REITS



(B) SAFEST REITS



Note: The maps show the county-level distribution of REIT property holdings. Panel A shows the number of holdings in each county for REITs in the top portfolio (riskiest REITs), while Panel B shows the distribution for REITs in the bottom portfolio (safest REITs). The sample period is 2021.

TABLE A.2: SUMMARY STATISTICS OF FACTORS

	mean	sd	p25	p75	count
Market (SPY)	0.0003	0.0124	-0.0046	0.0059	5598
TCF: Stranded Asset	-0.0003	0.0142	-0.0074	0.0075	5598
PCF: REIT-based	-0.0001	0.0041	-0.0024	0.0023	2831

Note: The sample period is 2002-2023 and all factors are daily.

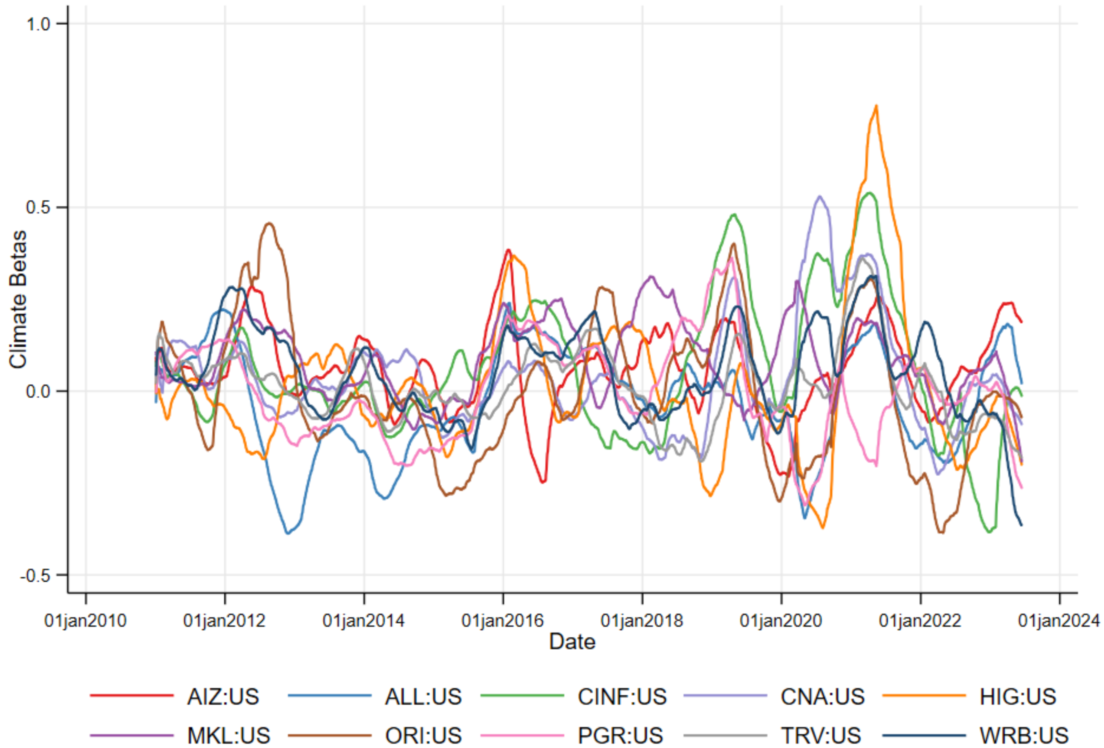
TABLE A.3: CORRELATION OF FACTORS

Panel A: Pearson Factor Correlations	(1)	(2)	(3)
Market Risk Factor			
(1) SPY ETF	1.00		
Transition Risk Factor			
(2) Stranded Asset	0.13	1.00	
Physical Risk Factor			
(3) REIT-based	-0.02	-0.00	1.00

Panel B: Orthogonalizd to Fama-French Three Factors	(1)	(2)	(3)
Market Risk Factor			
(1) SPY ETF	1.00		
Transition Risk Factor			
(2) Stranded Asset	-0.07	1.00	
Physical Risk Factor			
(3) REIT-based	0.02	-0.04	1.00

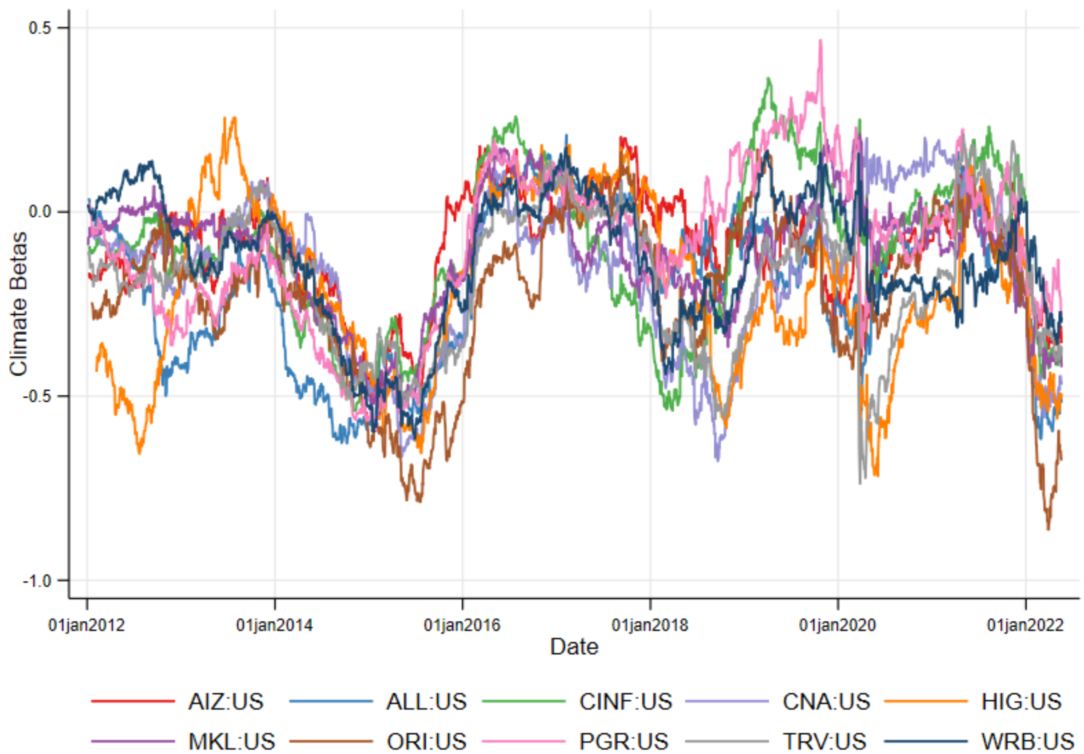
Note: Panel A shows the daily factor correlations for the period 2002 to 2020. Panel B shows the corresponding factor correlations after orthogonalizing each factor with respect to the Fama-French market, size and value factors.

FIGURE A.4: PHYSICAL CLIMATE BETA OF P&C INSURERS IN THE U.S.



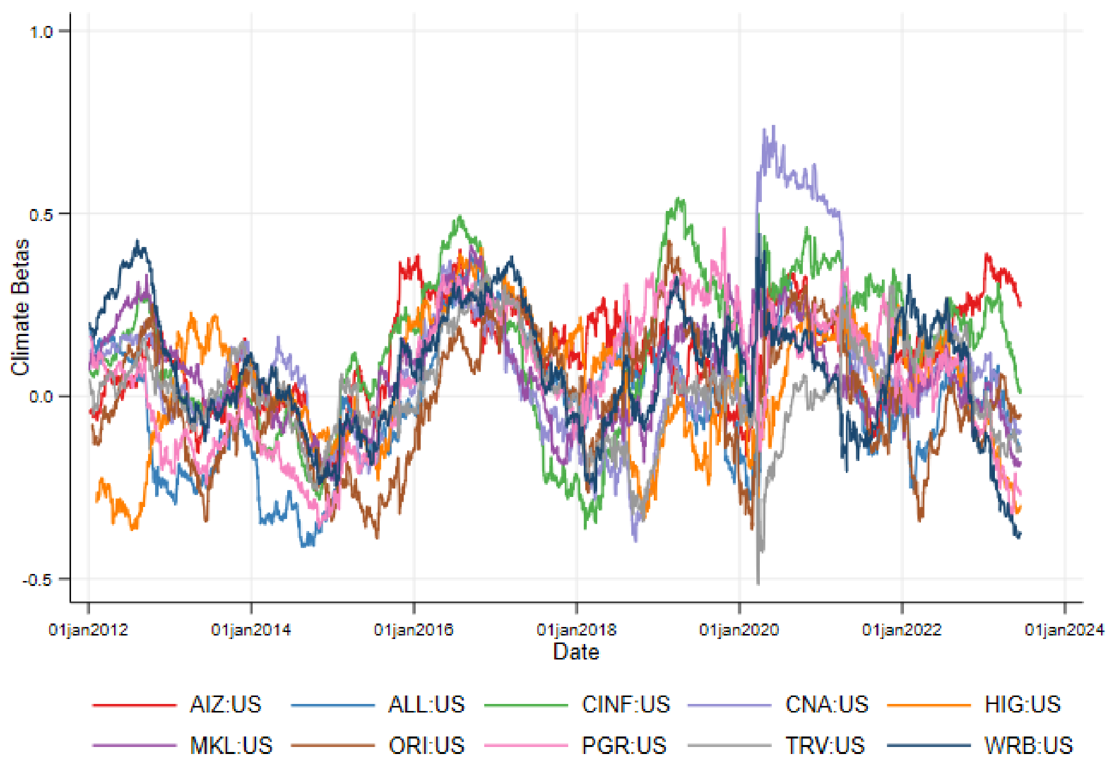
Note: Climate beta of P&C insurers in the U.S.. The large insurers are the to P&C insurers in Table A.1. The sample period is from January 2011 to December 2022.

FIGURE A.5: PHYSICAL CLIMATE BETA OF P&C INSURERS IN THE U.S. (CONTROLLING FOR LTG, CRD, IYR, AND COVID)



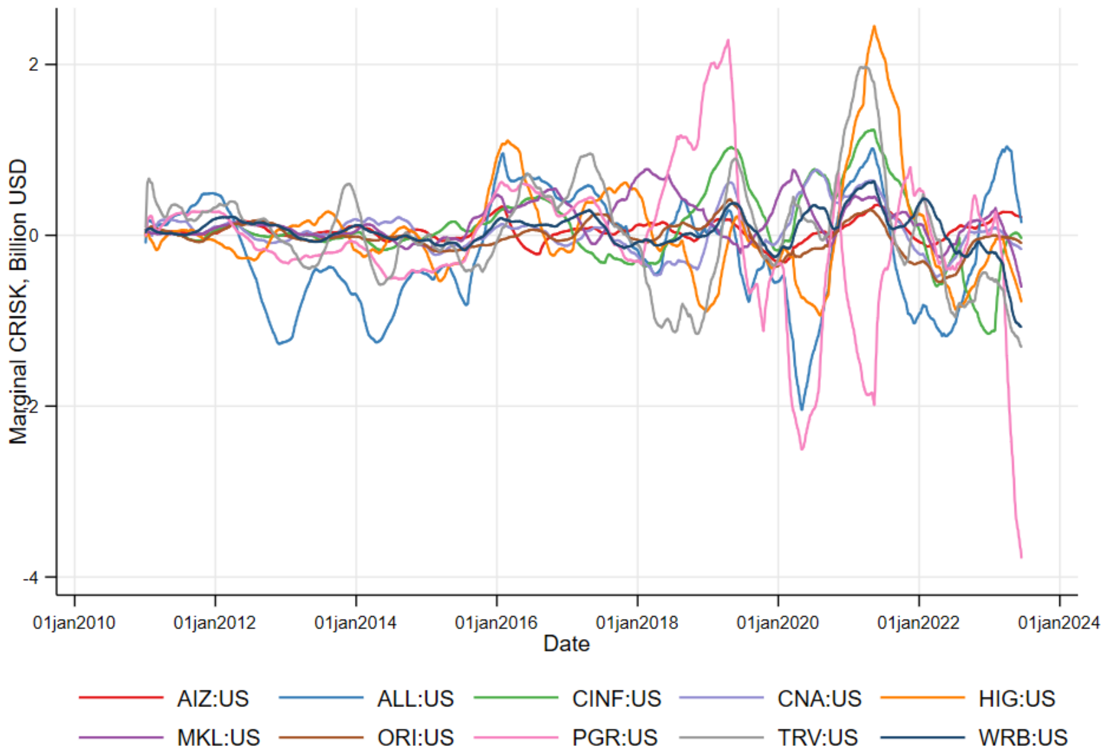
Note: Climate beta of large P&C insurers in the U.S.. The sample period is from January 2011 to December 2022. The large insurers are the top large P&C insurers in Table A.1. The Covid factor is the value-weighted average of the four most affected industries during Covid, as identified by Fahlenbrach et al. (2021): oil and gas extraction, support activities for mining, pipeline transportation, and amusement, gambling, and recreation.

FIGURE A.6: PHYSICAL CLIMATE BETA OF P&C INSURERS IN THE U.S. (CONTROLLING FOR SMB, HML, CMA, AND RMW)



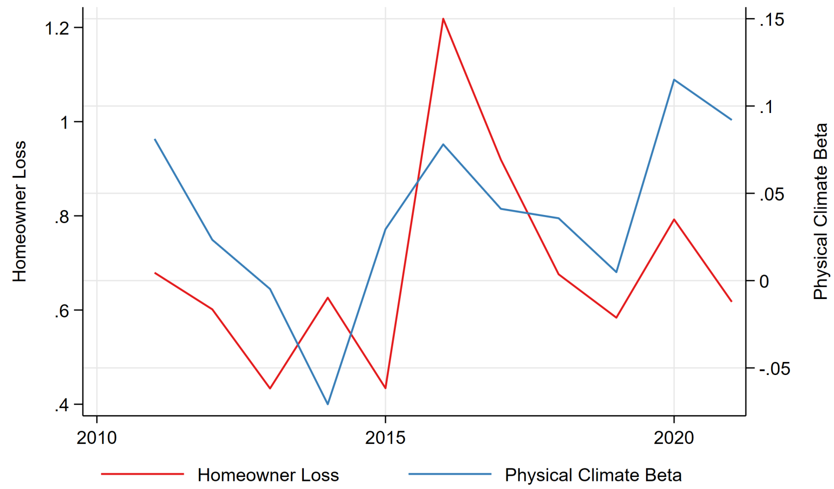
Note: Climate beta of large P&C insurers in the U.S.. The sample period is from January 2011 to December 2022. The large insurers are the top large P&C insurers in Table A.1.

FIGURE A.7: PHYSICAL MARGINAL CRISK OF P&C INSURERS IN THE U.S.



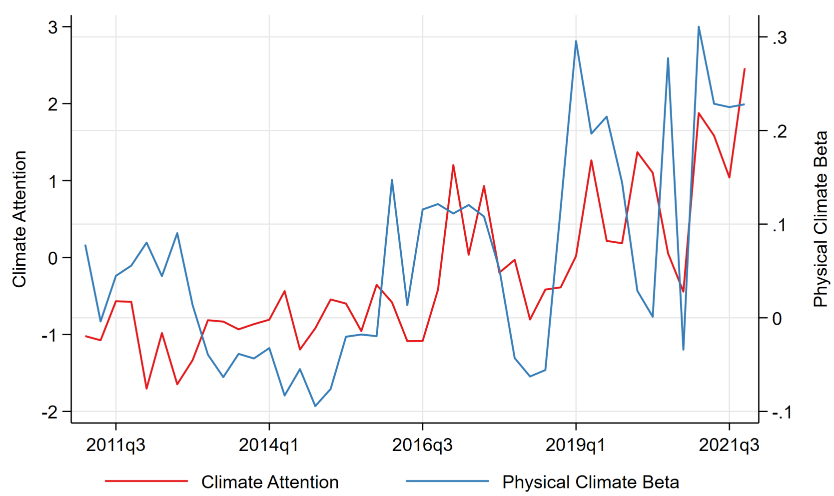
Note: Physical marginal CRISK of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in Table A.1. The sample period is from January 2011 to December 2022.

FIGURE A.8: P&C INSURERS' PHYSICAL CLIMATE BETA AND HOMEOWNER LOSS



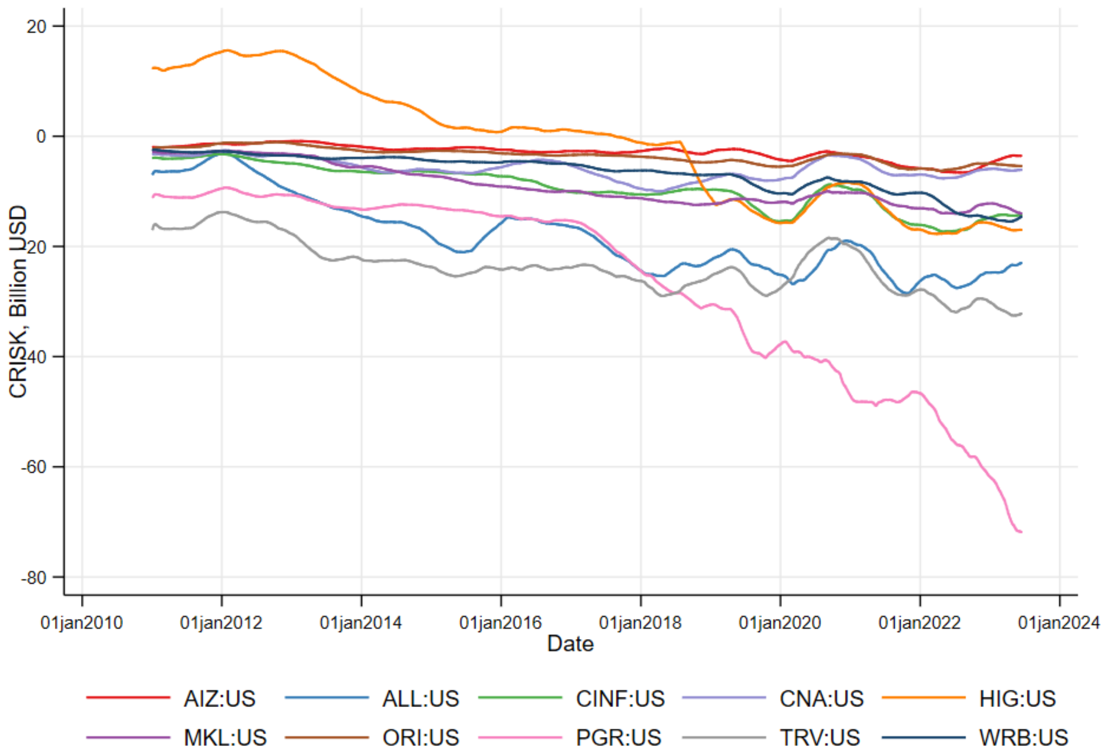
Note: Annual average physical climate beta and homeowner loss from 2011 to 2021. Homeowner loss is calculated as the ratio of loss incurred to premium. The sample insurers are the top large P&C insurers in Table A.1, with the average being equally weighted. The correlation is 0.4291.

FIGURE A.9: P&C INSURERS' PHYSICAL CLIMATE BETA AND CLIMATE ATTENTION



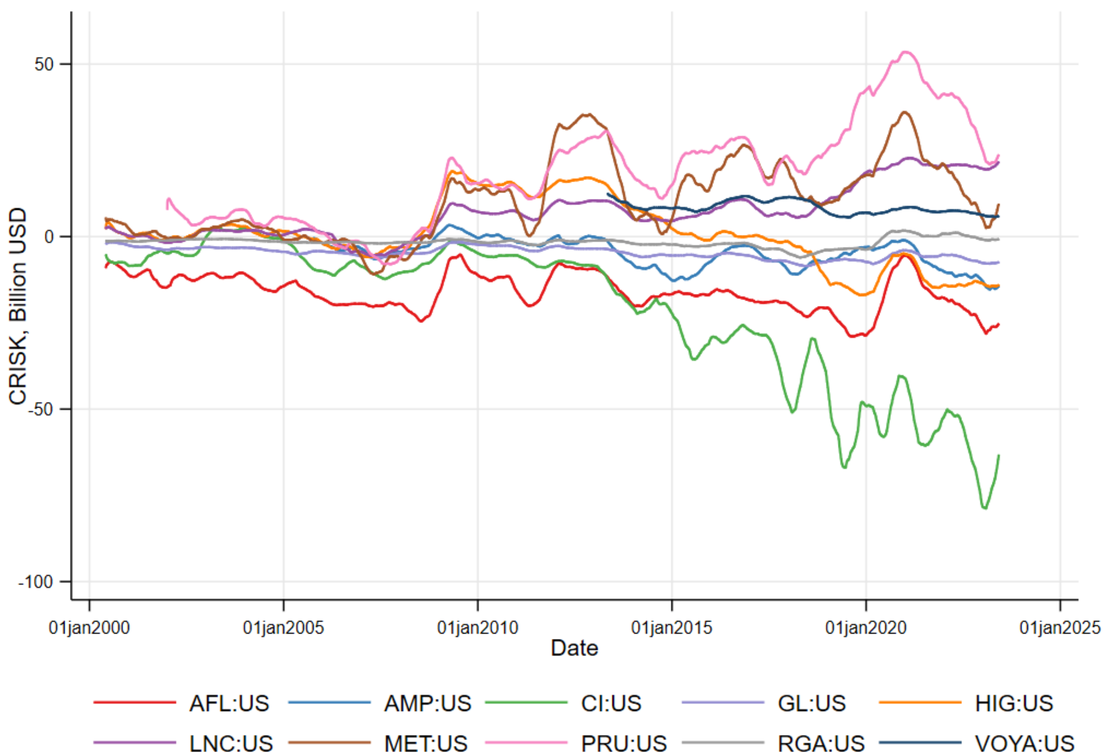
Note: Quarterly average physical climate beta and climate attention from 2011 to 2022. The sample insurers are the top large P&C insurers in Table A.1, with the average being equally weighted. The correlation is 0.5768.

FIGURE A.10: PHYSICAL CRISK OF P&C INSURERS IN THE U.S.



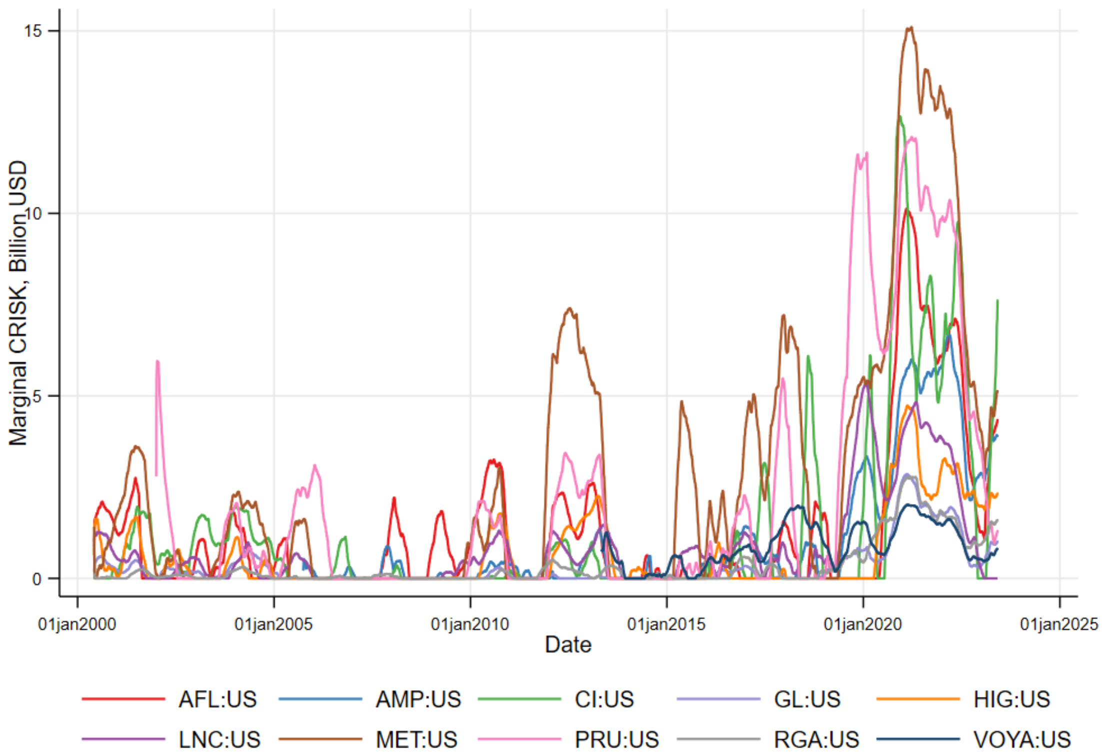
Note: Physical CRISK of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in Table A.1. The sample period is from January 2011 to December 2022.

FIGURE A.11: TRANSITION CRISK OF LIFE INSURES IN THE U.S.



Note: Transition CRISK of life insurers in the U.S.. The sample insurers are the top large life insurers in Table A.1. The sample period is from June 2000 to December 2022.

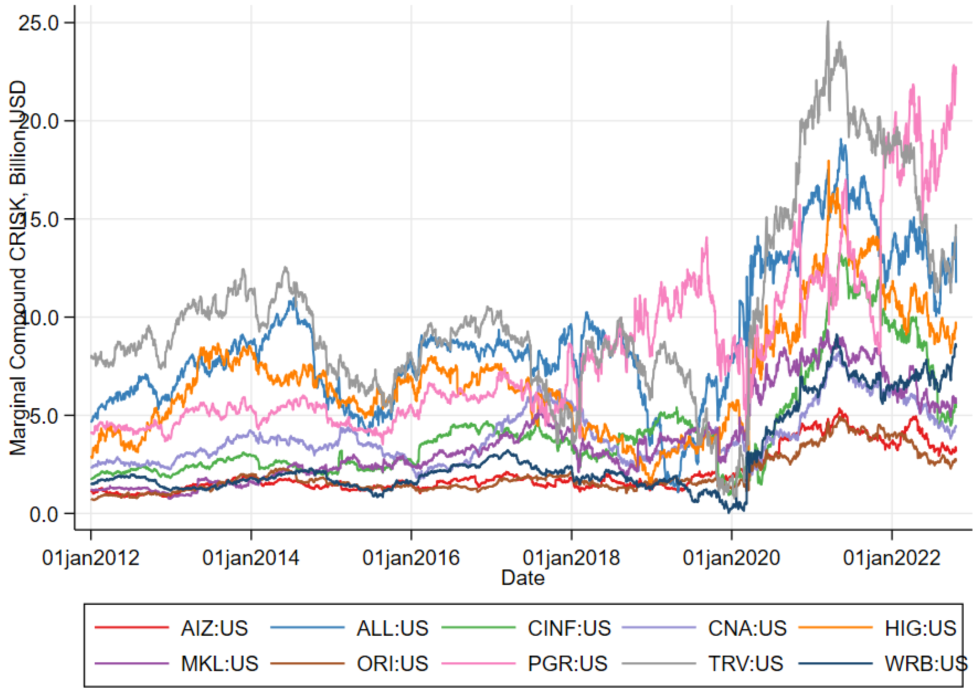
FIGURE A.12: TRANSITION MARGINAL CRISK OF LIFE INSURES IN THE U.S.



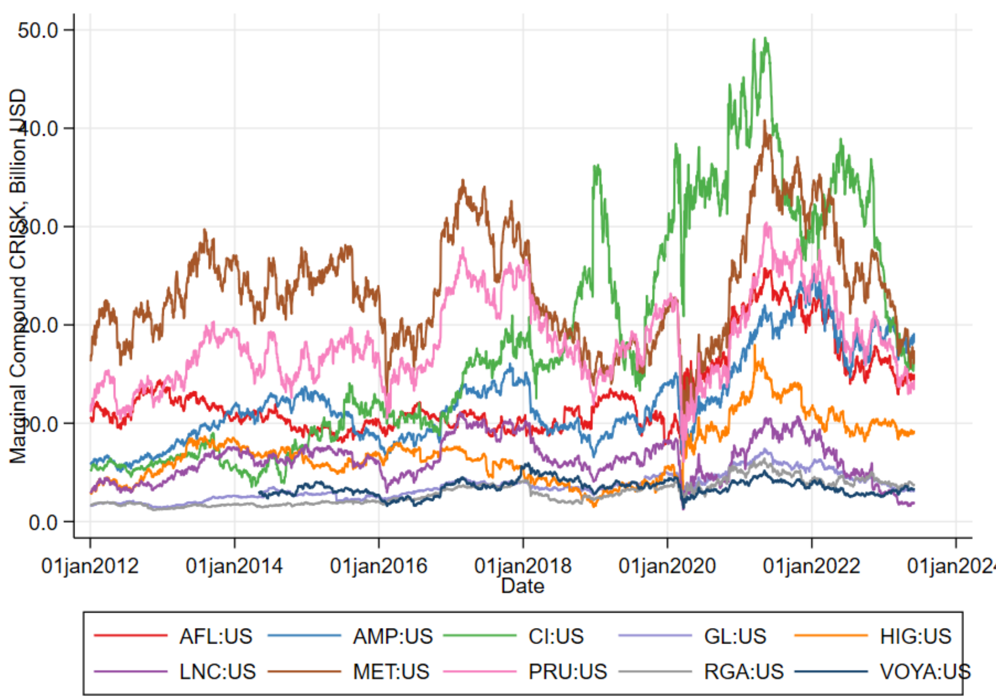
Note: Transition marginal CRISK of life insurers in the U.S.. The sample insurers are the top large life insurers in Table A.1. The sample period is from June 2000 to December 2021.

FIGURE A.13: MARGINAL COMPOUND CRISK

(A) ESIMATED MCCRISK OF TOP 10 P&C INSURERS



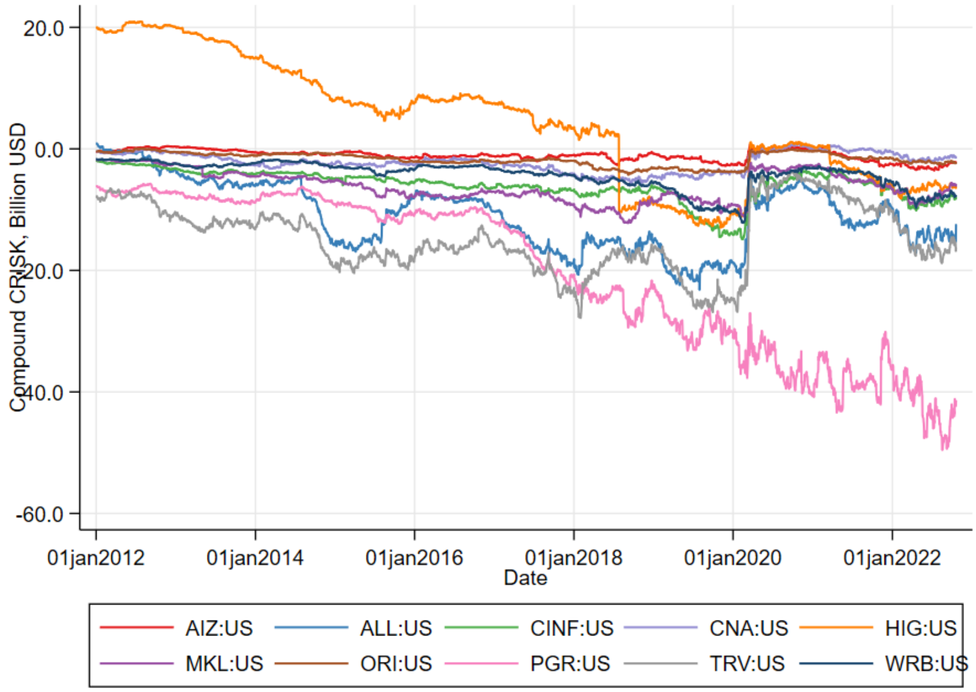
(B) ESIMATED MCCRISK OF TOP 10 LIFE INSURERS



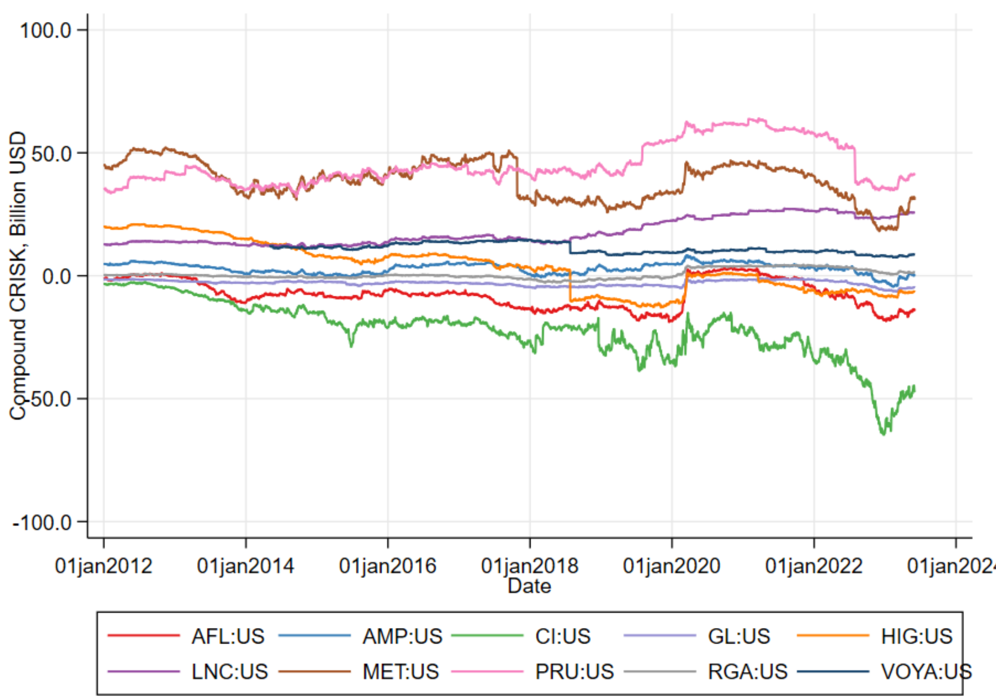
Note: Panel A displays the estimated compound marginal CRISK of P&C insurers in the U.S.. The sample insurers are the top large P&C insurers in Table A.1. The sample period is from January 2012 to December 2021. Panel B exhibits the estimated marginal compound CRISK of life insurers in the U.S.. The sample insurers are the top large life insurers in Table A.1. The sample period is from January 2012 to December 2021.

FIGURE A.14: 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 A.1. The sample period is from January 2012 to December 2021. 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 A.1. The sample period is from January 2012 to December 2021.

B Nonlisted Insurers

Listed insurers' market share is about 50% as of 2022. In this section, we sketch an approach to estimate the CRISK of unlisted insurers. We also provide an estimate of mCRISK based on back-of-the envelope calculations. To compute the physical risk exposure of non-listed insurers, we build upon the relationship between the physical climate beta, the policy portfolio physical climate beta, and insurer-level characteristics. Since the policy composition and characteristics are observable for nonlisted insurers, we impute their physical climate beta based on the estimation result of specification (2) from Table 2 without insurer fixed effects.

One potential concern is the difference between listed and nonlisted insurers. While we cannot fully address this issue, we test the stability of the coefficients by iteratively excluding one insurer at a time from the sample to ensure that the results in Table 2 are not driven by any single insurer. Figure B.1 below plots the coefficient estimate when one insurer is dropped at a time, and it suggests that the main coefficient (on policy portfolio climate beta) is indeed stable. Similarly, we find that other coefficients are also stable, suggesting that the they are not driven by any particular insurer.

Applying the coefficient estimates from specification (2) of Table 2 to nonlisted insurers, we find that their average climate beta is lower than that of listed insurers (see Figure B.2). This is primarily driven by the negative coefficient on size, indicating that smaller insurers generally exhibit higher climate betas.

To compute the market value of equity, we apply the listed P&C insurers' average market-to-book ratio. Then, we can compute the mCRISK of non-listed insurers as:

$$mC\tilde{R}ISK_{it} = (1-k) \cdot \text{Book Equity}_{it} \cdot (\text{Avg Market-to-book Ratio}_t) \cdot LR\tilde{M}ES_{it}$$

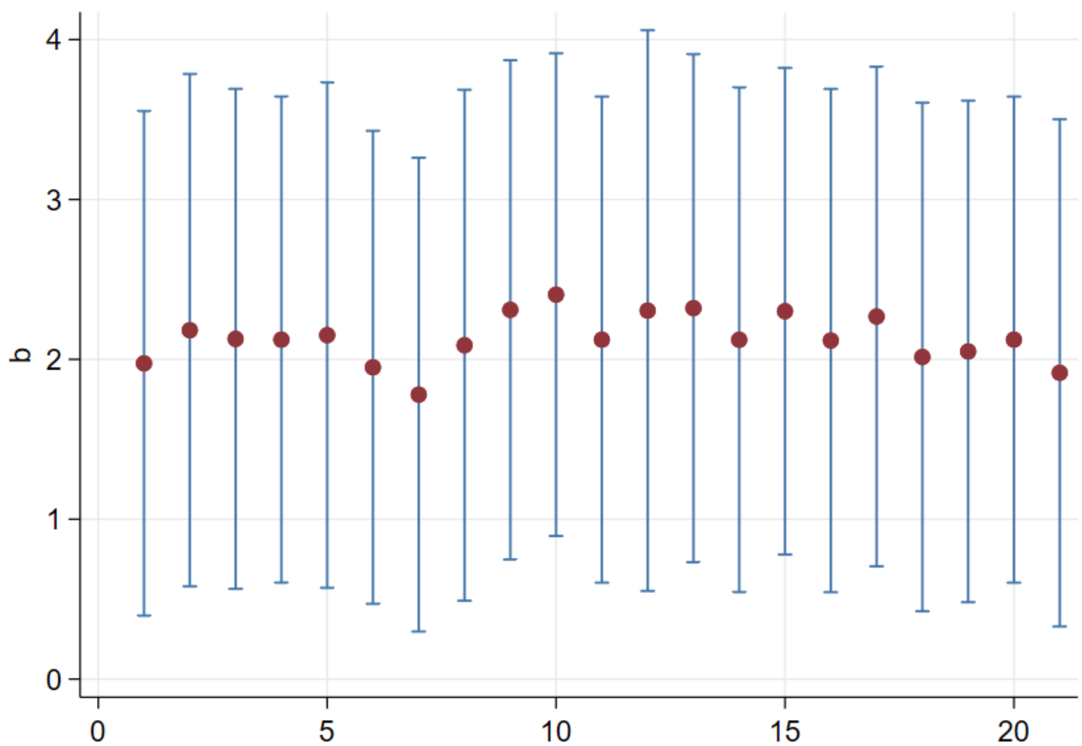
where

$$LR\tilde{M}ES_{it} = 1 - \exp\left(\hat{\beta}_{it}^{Climate} \log(1-\theta)\right)$$

and $\hat{\beta}_{it}^{Climate}$ denotes the fitted value of climate beta based on the insurer i's portfolio beta and characteristics at time t.

Based on this back-of-the-envelope calculation, we estimate that the non-listed insurers' aggregate mCRISK is \$1.59 billion as of the end of our sample period, 2021. If we apply the minimum and maximum values of market-to-book ratio instead of the average value, we estimate that the nonlisted insurers' aggregate mCRISK ranges between \$0.6 and \$3.6 billion, as of 2021.

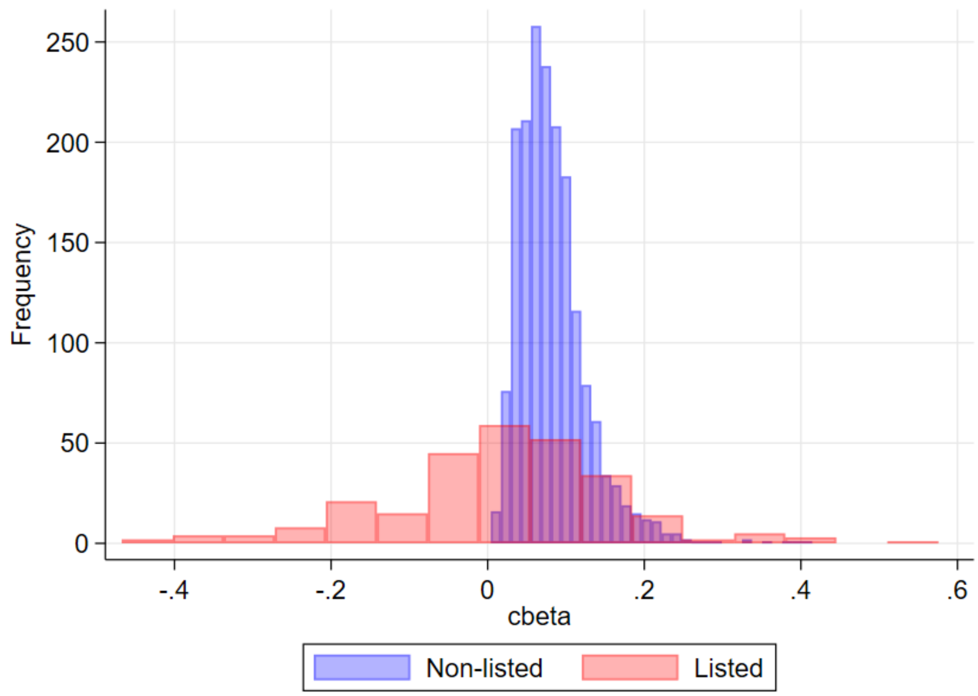
FIGURE B.1: COEFFICIENT STABILITY



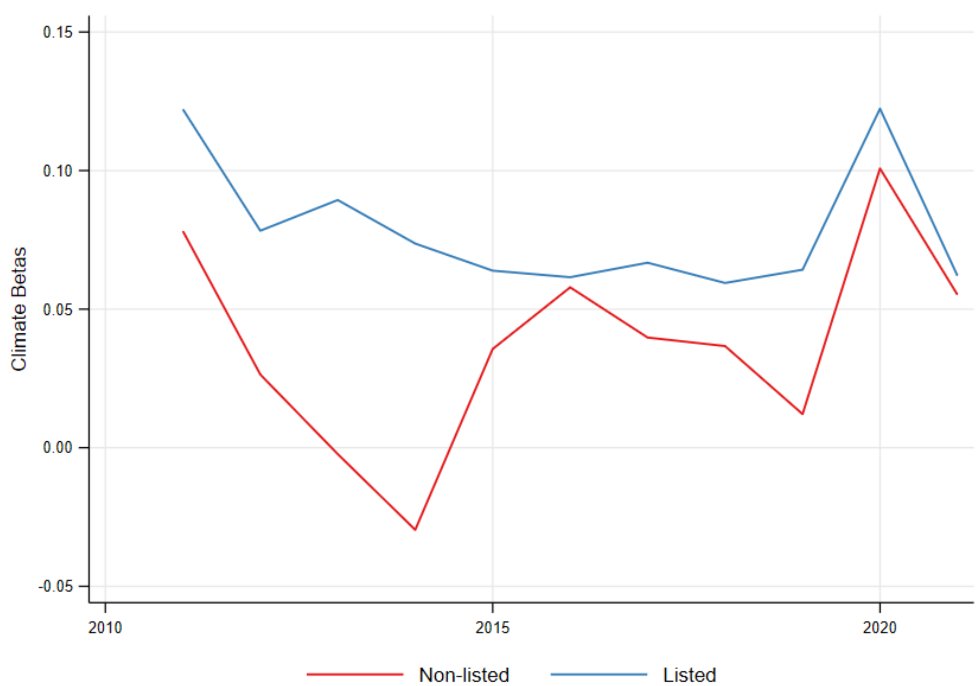
Note: Coefficient estimates of Policy Portfolio Physical Climate Beta, excluding one insurer at a time. Each dot represents the coefficient estimate (b) after dropping a single insurer. The band shows 95% confidence interval.

FIGURE B.2: PHYSICAL CLIMATE BETA OF LISTED AND NON-LISTED P&C INSURERS

(A) DISTRIBUTION OF INSURERS' CLIMATE BETA



(B) CLIMATE BETA OVER TIME



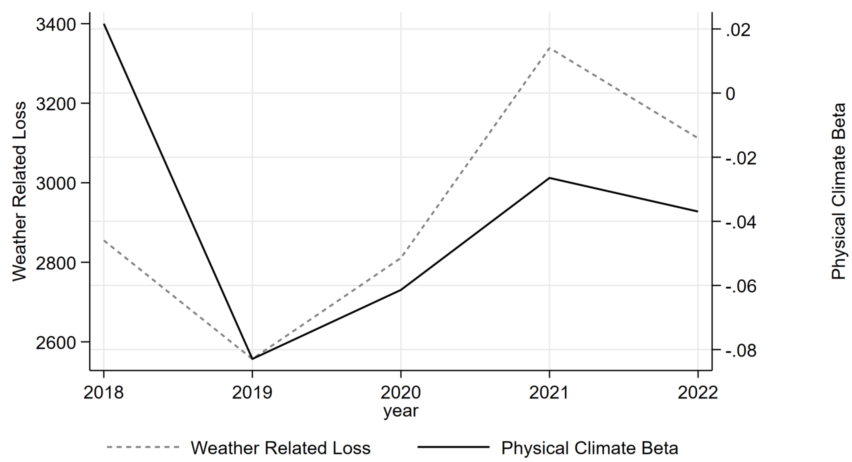
Note: Climate beta of listed and non-listed P&C insurers in the U.S.. Non-listed insurers' betas are derived from coefficient estimates in the specification (2). Panel (A) presents the histogram of all insurers' betas. Panel (B) reports the weighted average of listed and non-listed insurers' physical climate betas over time. The sample period is from January 2011 to December 2021.

Internet Appendix to
“Physical Climate Risk Factors and an Application to Measuring Insurers’ Climate Risk Exposure"

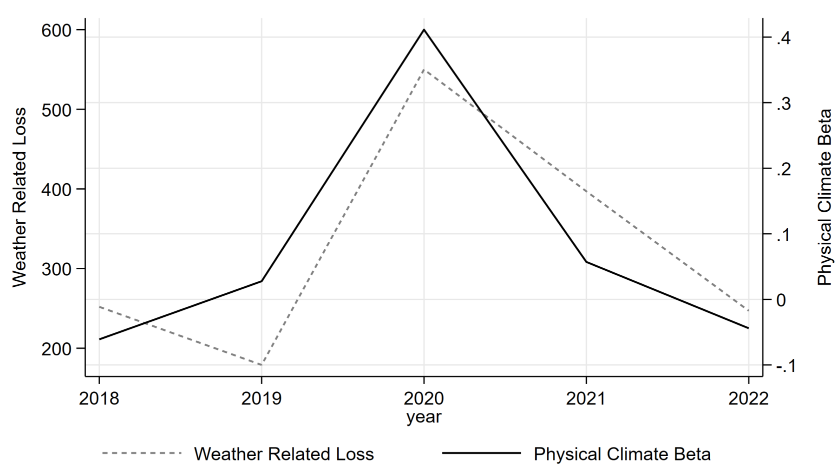
IA.A Physical Climate Beta amd Weather-Related Loss

FIGURE IA.A.1: PHYSICAL CLIMATE BETA VS. WEATHER-RELATED LOSS

(A) ALLSTATE



(B) CIGNA



Note: Annual physical climate beta and weather-related loss reported in 10K reports for P&C insurers AllState and Cigna.

IA.B 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 dependence" is defined as:

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

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

$$P(x < -\theta_x) \cup P(y < -\theta_y) = 2u - u \cdot \lambda(u) = \alpha \tag{20}$$

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 (20) (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:

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

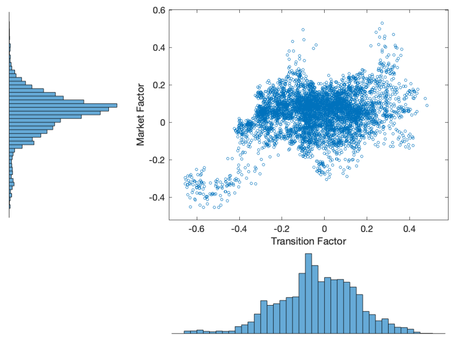
where

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

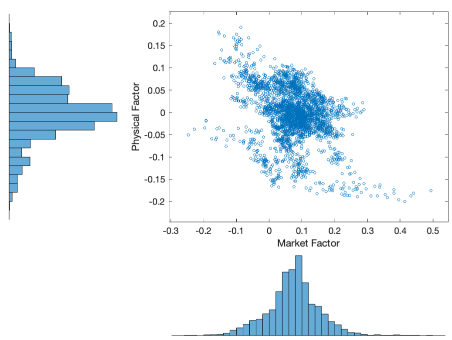
Based on the empirical λ estimates visualized in Figure 9, $\bar{\lambda}_{xyz} = 0, \bar{\lambda}_{xy} = 0.13, \bar{\lambda}_{xz} = 0, \bar{\lambda}_{yz} = 0$, and therefore $u^* = 0.01/(3 - 0.13) = 0.0035$.

FIGURE IA.B.1: PAIRWISE JOINT DISTRIBUTIONS

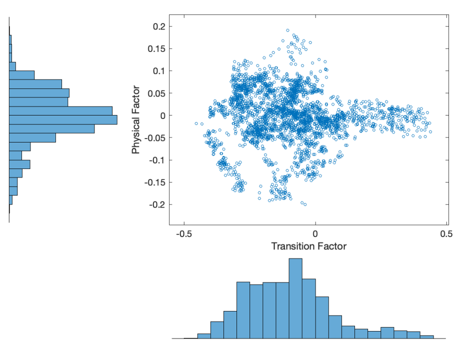
(A) MARKET VS. TRANSITION RISK



(B) MARKET VS. PHYSICAL RISK



(C) TRANSITION VS. PHYSICAL



Note: Panel (A) shows the scatter histogram of the market risk factor and the transition risk factor based on 2001-2021 daily returns. Panel (B) and (C) show those of market and physical risk factors and transition and physical risk factors, respectively based on 2011-2021 daily returns.

IA.C Municipal Bond Return Estimation

Our estimation of the monthly return series is based on Auh et al. (2022) and follows insights from repeat-sales models in the housing market. It is based on the following model:

$$R_{i,b:s} = \sum_{t=b+1}^{s} R_t^c + e_{i,b:s}$$

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

IA.D Alternative Physical Risk Factors

To capture actual disaster loss, We utilize monthly data from National Oceanic and Atmospheric Administration (NOAA) 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, covering hazards including hurricanes, tornadoes, floods, and wildfires. Table IA.D.1 shows the summary statistics of property damage by hazard type. With these property loss data, we assess the risk exposure of each insurer.

TABLE IA.D.1: NATURAL DISASTER DATA DESCRIPTIVE 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

Note: Summary statistics of SHELDUS country-level property damage data. The sample period is 2000-2019.

Insurer Premium Factor is 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:

$$RISK_{i,t} = \sum_{s \in S} \left[\left(\frac{DPE_{i,s,t-1}}{\sum_{s \in S} DPE_{i,s,t-1}} \right) \times \text{Property Damage}_{s,t-1} \right] \times \frac{1}{ME_{i,t-1}} \tag{21}$$

where $DPE_{i,s}$ denotes the direct premium earned by insurer i in state s, 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 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.

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:

$$\text{Loss-to-Equity}_{i,t} = \frac{\sum_j \bar{\rho}_{i,j,t-1} DPE_{i,j,t-1}}{ME_{i,t-1}} \tag{22}$$

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

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

and $\bar{\rho}$ is exponentially smoothed risk weights.[23] 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.

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:

$$RBC_{i,t} = \frac{\text{Equity}_{i,t}}{\text{Required Equity}_{i,t}} \tag{23}$$

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

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

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.[24]

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[25] 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

[24] We document supporting evidence in **??** showing that P&C insurers with high operational exposure to physical risk experienced higher incurred losses.

[25] 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 $30/\sum_{i=1}^{30} i$

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 are evaluated based on the High Climate Change Scenario (RCP 8.5 [26]) 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 IA.E.4 demonstrates the event study of factors' response to physical climate shocks.

[26] 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.

IA.E Physical Risk Factor Event Studies: Robustness Tests

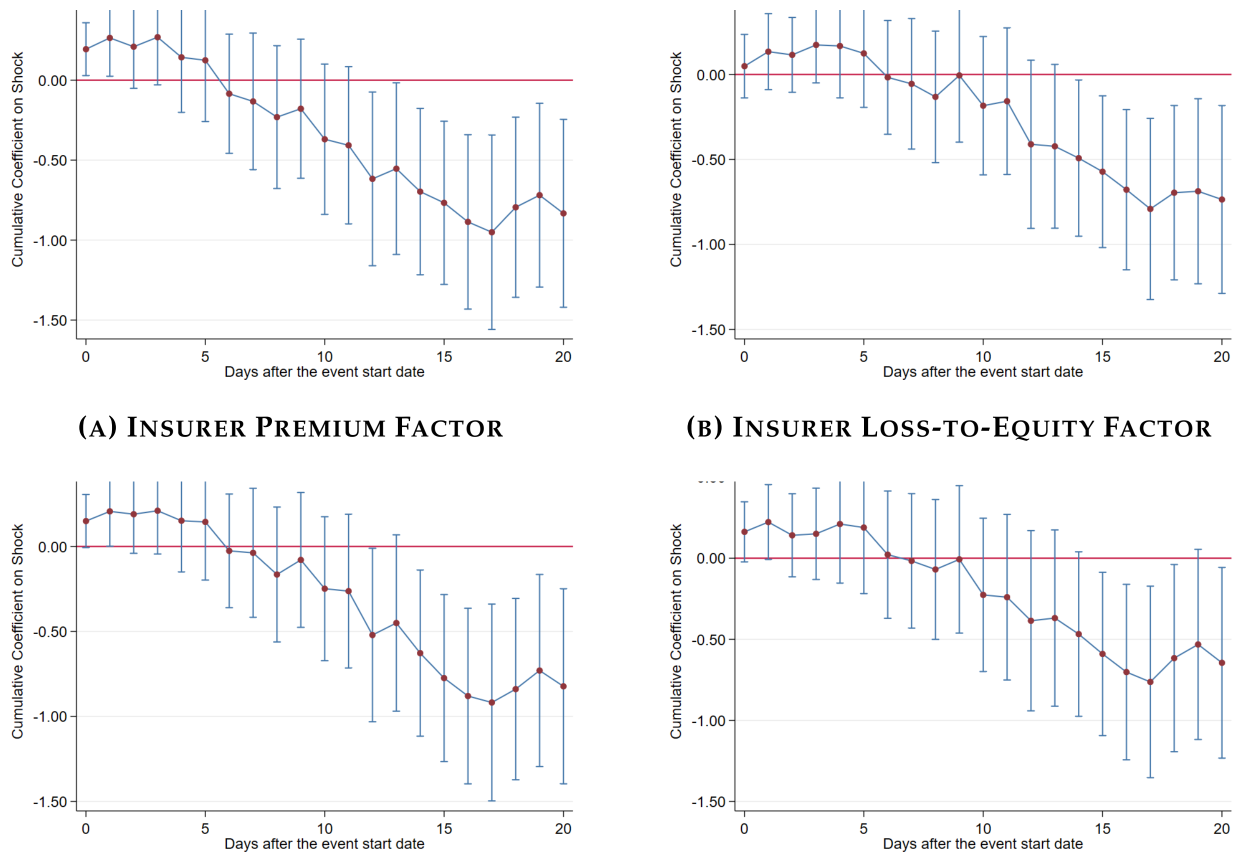
We conduct a series of robustness tests to ensure the reliability of the event study results. First, we find that the factors constructed using the alternative approaches to computing $RISK$, such as taking the standard deviation of property damage or subtracting the earned premium, exhibit similar responses to natural disaster events (Appendix Figure IA.E.1). 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 IA.E.2). 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 IA.E.3).

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 3.1 and Section IA.D). Appendix Figure IA.E.1 shows that the factors derived through alternative methods for calculating $RISK$ demonstrate comparable responses to natural disaster events.

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 IA.E.2 suggests that all four factors decline after natural disaster events and the results are robust after dropping the flood events from the sample.

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 IA.E.3 continues to demonstrate consistency even with this modified approach.

FIGURE IA.E.1: ROBUSTNESS TEST: EVENT STUDY WITH ALTERNATIVE PHYSICAL RISK FACTORS



(A) INSURER PREMIUM FACTOR

(B) INSURER LOSS-TO-EQUITY FACTOR

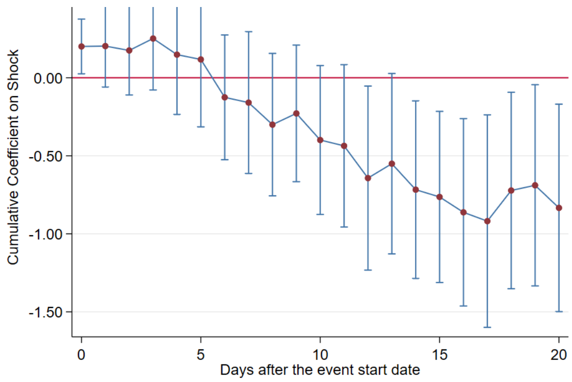
(C) LOSS DEVIATION FACTOR

(D) NET DAMAGE FACTOR

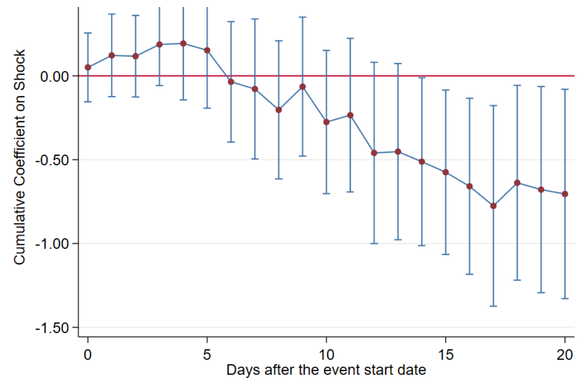
Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + \theta MKT_t + \epsilon_t$. $shock_t$ takes the value of 1 if it was the start date of a natural disaster event, and a value of 0 if there was no disaster on day t. Each physical risk factor series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

Consider the 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 IA.D. 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.

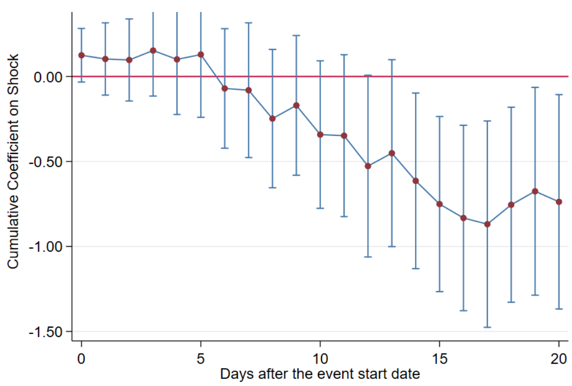
FIGURE IA.E.2: ROBUSTNESS TEST: EVENT STUDY WITHOUT FLOODING



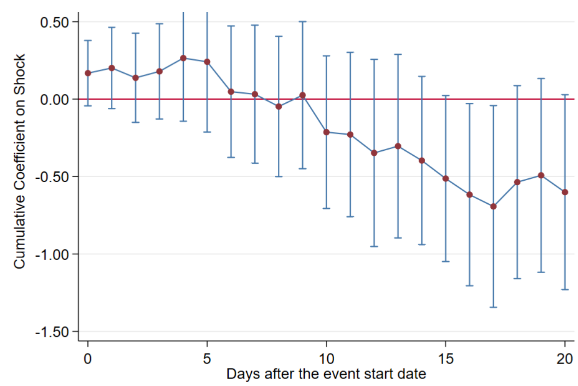
(A) INSURER PREMIUM FACTOR



(B) INSURER LOSS-TO-EQUITY FACTOR



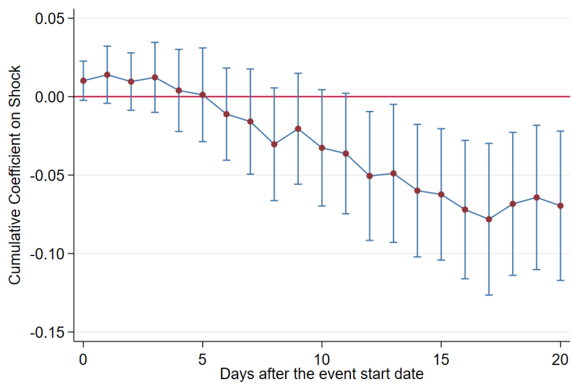
(C) LOSS DEVIATION FACTOR



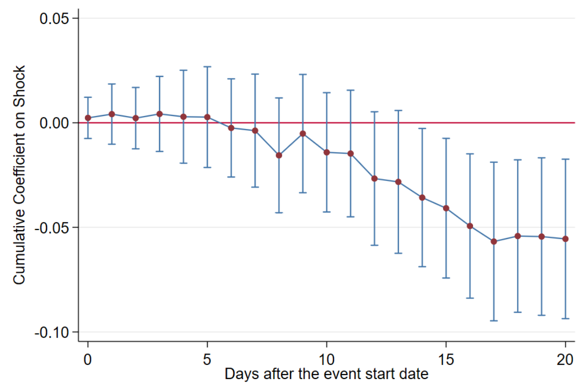
(D) NET DAMAGE FACTOR

Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + \theta MKT_t + \epsilon_t$. $shock_t$ 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.

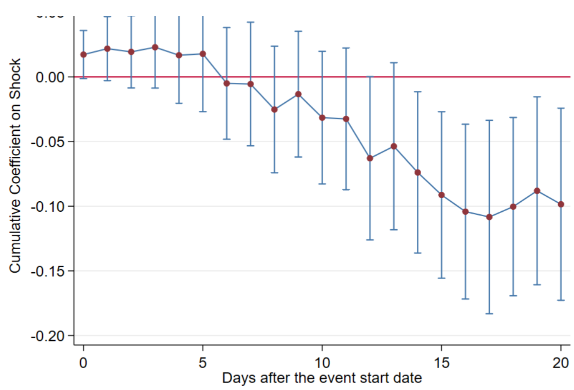
FIGURE IA.E.3: ROBUSTNESS TEST: EVENT STUDY WITH DAMAGE SIZE



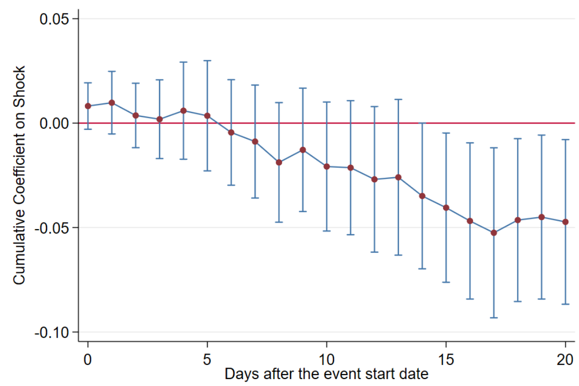
(A) INSURER PREMIUM FACTOR



(B) INSURER LOSS-TO-EQUITY FACTOR



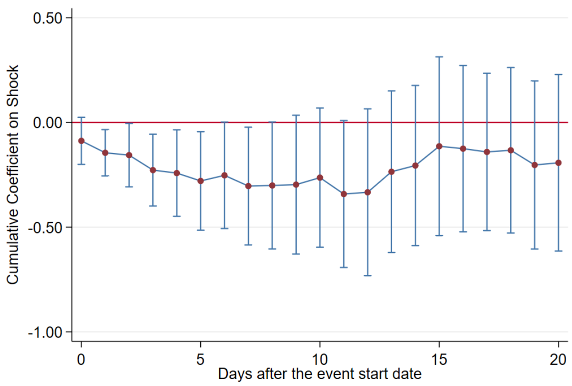
(C) LOSS DEVIATION FACTOR



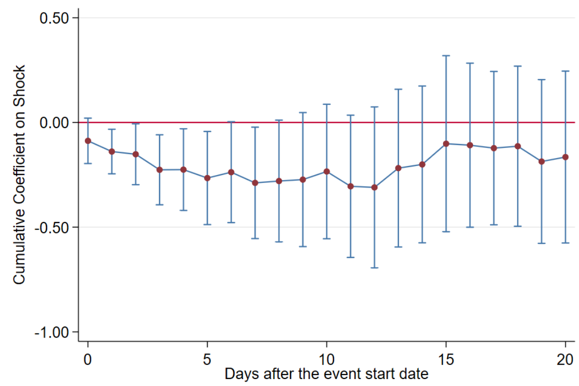
(D) NET DAMAGE FACTOR

Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + \theta MKT_t + \epsilon_t$. $shock_t$ 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.

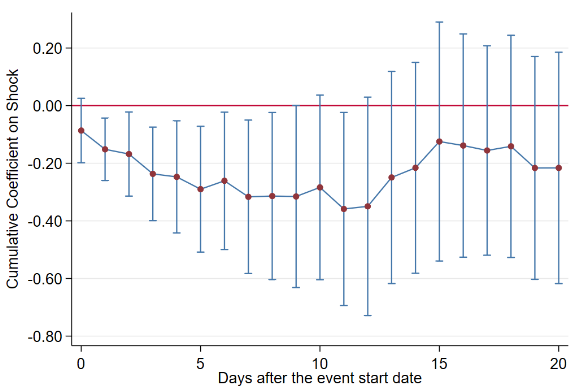
FIGURE IA.E.4: ROBUSTNESS TEST: EVENT STUDY WITH DIFFERENT TIME HORIZONS



(A) SHORT-TERM (2020)



(B) MEDIUM-TERM (2030)



(C) LONG-TERM (2050)

Note: Cumulative coefficient γ on $shock_t$ in $PCF_t = \alpha + \sum_{n=0}^{20} \gamma_n shock_{t-n} + \theta MKT_t + \epsilon_t$. $shock_t$ 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.