CFR Working Paper NO. 23-08

Extreme Weather Risk and the Cost of Equity

A. Braun • J. Braun • F. Weigert

centre for financial Research
cologne

Extreme Weather Risk and the Cost of Equity

Alexander Braun[a], Julia Braun[a], Florian Weigert*[b]

[a] *Institute of Insurance Economics, University St.Gallen*
[b] *University of Neuchatel*

Abstract

We examine if extreme weather exposure impacts firms' cost of equity. Motivated by a consumption-based asset pricing model with heterogeneous agents, we reveal the existence of an extreme weather risk premium in the cross-section of stock returns. In the period from 1995 to 2019, domestic U.S. stocks with the most negative sensitivity to thunderstorm losses earned excess returns of 6.5% p.a. over those with the most positive sensitivity. This premium can neither be explained by risk factors from standard asset pricing models nor by firm characteristics. Our results reveal a novel link between climate risk and firm value.

Keywords: Extreme Weather Risk, Climate Risk, Cost of Equity, Empirical Asset Pricing

JEL: C12, G01, G11, G12, G17

***Contact details:** Alexander Braun is Associate Professor of Insurance and Capital Markets as well as Director of the Institute of Insurance Economics at the University of St. Gallen, Tannenstrasse 19, CH-9000 St. Gallen, Switzerland. Julia Braun is a Ph.D. student in Finance at the University of St. Gallen. Alexander Braun and Julia Braun are not related. They share the same surname by coincidence. Florian Weigert is Professor of Financial Risk Management at the Institute of Financial Analysis, University of Neuchâtel, Rue A.-L. Breguet 2, CH-2000 Neuchâtel. Florian Weigert is also affiliated with the Centre for Financial Research (CFR) in Cologne and would like to thank the CFR for their continuous support. The authors can be contacted via E-mail: alexander.braun@unisg.ch, julia.braun@unisg.ch, and florian.weigert@unine.ch. **Acknowledgements:** We thank Jeff Bohn, Martin Brown, Lauren Cohen, Benjamin Collier, Randy Dumm, Martin Eling, Cameron Ellis, Lisa Goldberg, Martin Grace, Ralph Kojien, Carolyn Kousky, Howard Kunreuther, Zacharias Sautner, and Jessica Wachter for their helpful comments. We also thank the participants of the SFI Research Days 2023, the European Group of Risk and Insurance Economists (EGRIE) Meeting 2022, the American Risk and Insurance Association (ARIA) Meetings 2021 and 2023, the German Finance Association (DGF) Meeting 2021, the Consortium for Data Analytics in Risk (CDAR) seminar at the University of California at Berkeley 2021, the World Risk and Insurance Economics Congress (WRIEC) 2020, the Temple University research seminar, and the Wharton Risk Management and Decision Processes Center seminar.

1. Introduction

The economic repercussions of natural disasters have become increasingly severe. Ongoing population growth, urban sprawl into hazard-prone areas such as coastlines and flood plains and, most recently, anthropogenic climate change have led to a clear upward trend in disaster losses throughout the last three decades (Botzen et al., 2019). The risk has reached alarming magnitudes: From 2017 to 2019, natural catastrophes caused combined economic damages of about USD 600 billion around the world (Swiss Re, 2020). Extreme weather perils, such as storms and floods, have increased threefold in frequency since the 1980s and are one of the largest contributors to worldwide disaster losses (Hoeppe, 2016; Swiss Re, 2022). This trend reached its preliminary peak in the first half of 2023, in which the total losses from U.S. thunderstorms exceeded $35 billion (Swiss Re, 2023).

Although climate change is commonly referred to as one of the most acute threats of the 21st century, its implications for financial markets are not yet fully understood. In this paper, we connect physical climate risk to stock prices and study whether extreme weather exposure has become a driver of firms' cost of equity. We focus on severe thunderstorms (convective storms) because they are economically relevant, frequent, and geographically widespread. Moreover, the direct losses (damages to tangible assets) and indirect losses (e.g., supply chain disruptions) caused by these extreme weather events are regularly underinsured. These aspects suggest an impact of severe storm risk on firm performance and makes it a candidate for a key common risk factor that drives the cost of equity.

To motivate the existence of a risk premium for idiosyncratic storm risk in the cross-section of stock returns theoretically, we suggest an extension to the consumption-based asset pricing model of Constantinides & Duffie (1996). In this framework, heterogeneous agents face an ex ante exposure to idiosyncratic consumption shocks that ex post materialize only among a few. Consumption losses from these shocks are assumed to be uninsurable. Extreme weather events are a prime example of such shocks for which risk sharing is limited, because there are substantial protection gaps among U.S. households and businesses regarding storm and (associated) flood losses. Our theory predicts that the expected return of an individual asset depends on (i) the correlations between macroeconomic fundamentals (consumption growth, consumption inequality) and log storm loss growth ($LSLG$) as well as (ii) the correlation between the excess returns on risky assets and $LSLG$. Both of these necessary conditions for a storm risk premium are empirically testable.

We start our empirical analysis by investigating the correlations between $LSLG$ and log consumption growth on the one side as well as $LSLG$ and consumption inequality on the other side. $LSLG$ (per capita) is computed from a long-term data set of U.S. storm losses provided by the Spatial Hazard Events and Losses Database for the United States. In addition, we apply non-durable goods and service consumption (per capita) as well as state-level income data from the U.S. Bureau of Economic Analysis (BEA) to estimate consumption growth and income inequality (as a proxy for consumption inequality). We find that – in the time span from 1995 to 2019 – the correlation between $LSLG$ and income inequality amounts to statistically significant 0.249 which satisfies our first necessary condition for the existence of a storm risk premium.[1]

[1] As the year 1995 marks a structural break in the time series of severe thunderstorm frequencies in the U.S., with a severely elevated activity in the past 25 years of our data, we focus our empirical tests on the time span from 1995 to 2019.

We then turn to examine the impact of storm risk on the cross-section of stock returns from 1995 to 2019. For this purpose, stock market and accounting data for U.S. domestic common stocks is gathered within the intersection of CSRP and Compustat.[2] We focus on only domestic firms as an international diversification of sales and assets is likely to immunize firms against local U.S. weather risk. We measure a stock's storm risk sensitivity (*LSLG* beta) on a monthly basis by means of a five-year rolling regression of the stock's excess returns on the Fama & French (1993) three-factor model, the Carhart (1997) momentum factor plus *LSLG*. Our objective is to relate a stock's individual *LSLG* beta to future raw and risk-adjusted returns with the expectation that negative *LSLG* beta stocks should bear a premium compared to positive *LSLG* beta stocks.[3] Indeed, results from value-weighted univariate portfolio sorts reveal that stocks in the quintile with the lowest (and negative) *LSLG* beta earn an average monthly excess return (return minus risk-free rate) of 1.007%, compared to 0.468% for stocks in the quintile with the highest (and positive) *LSLG* beta. Thus, the spread in mean excess returns attributable to the *LSLG* beta amounts to 0.538% per month and is statistically significant at the 5% level. When controlling for the widely used risk factors of the Carhart (1997) four-factor model, we obtain a slightly lower risk-adjusted return of 0.526% per month, which remains statistically significant at the 5% level. Annualized, this reflects a storm risk premium for the cross

[2]We follow Denis et al. (2002) and characterize a firm as domestic if it reports at least 90% of sales within U.S. borders.

[3]Depending on their business model, location, and degree of supply-chain integration, firms can both suffer or benefit from severe storms. Construction firms, e.g., may experience a surge in revenues in the aftermath of natural disasters (see, e.g., Döhrmann et al., 2017). Firms that suffer in the wake of severe thunderstorms exhibit a negative *LSLG* beta, whereas firms that benefit show a positive *LSLG* beta.

section of domestic stock returns of approximately 6.5%.

We continue to investigate whether the storm risk premium can be explained by other asset pricing risk factors put forward in the literature. Hence, we run time-series regressions using the Carhart (1997) model with the following extensions: the Chabi-Yo et al. (2018) crash risk factor, the Sadka (2006) liquidity factor, the Pástor & Stambaugh (2003) liquidity factor, the Bali et al. (2011) lottery factor, the Baker & Wurgler (2006) sentiment index, the Frazzini & Pedersen (2014) betting-against-beta factor, the Fama-French short- and long-term reversal factors, and the Fama & French (2015) operating profitability and investment factors. Our results indicate that none of these previously established factors accounts for the spread in mean excess returns earned by the zero investment portfolio of negative minus positive (NMP) *LSLG* beta stocks (the long-minus-short storm risk premium). Instead, the alpha in all time-series regressions is statistically significant throughout and varies between 0.454% and 0.779% per month.

We obtain similar results in value-weighted Fama & MacBeth (1973) regressions. The effect of the *LSLG* beta on the one-month ahead future return is statistically significant and economically strong when we control for a firm's market beta, size, book-to-market ratio, idiosyncratic volatility, coskewness, as well as the past annual and monthly return. For each additional unit in negative *LSLG* beta, the next-month return of a stock, on average, increases by 0.152 percentage points. Moreover, we observe that adding the long-minus-short storm risk return to the Fama & French (1993) and Carhart (1997) factor models leads to a statistically significant reduction of the pricing errors in the cross-section of 25 test portfolios sorted by size and momentum. We document the robustness of the storm risk premium in additional robustness tests throughout the paper.

Finally, we aim to rationalize the emergence and magnitude of the storm risk premium with additional empirical tests. First, we inspect the seasonality of thunderstorms and the accompanying level of the storm risk premium within a given year. Thunderstorms regularly hit the U.S. from April to October and generate the highest damages in quarter three (see, e.g., Trapp et al., 2007). We find that the average magnitude of the storm risk premium also peaks during the third quarter. We interpret this result as a confirmation of the risk-based nature of the premium, indicating that investors of storm-risky stocks are compensated exactly when these stocks are most likely to decline in value. Second, we investigate the relationship between the storm risk premium and firms' geographic locations. To this end, we split the sample in two parts: firms headquartered in states that were historically exposed to significant thunderstorm activity and firms headquartered in other states. We detect a statistically significant storm risk premium only for the former. Third, we examine the role of salience in the compensation of storm risk for investors. For this purpose, we download all companies' 10-K, 10-K405 and 10-KSB filings from the EDGAR website of the U.S. Securities and Exchange Commission (SEC). We define salient firms as those that mention the keywords "severe storm", "storms", or "thunderstorm" (lowercase and capitalized) at least once in their financial statements of the past five years. In each month, we then dynamically split the sample into "salient" and "non-salient" firms based on a textual analysis and sort on *LSLG* betas in each of the two subsamples: The storm risk premium is emergent only for the salient firms.

Our results have several important implications. First and foremost, firms that are threatened by storm risk exhibit a higher cost of equity than their peers.

An elevated cost of equity may have a major impact on the firm's ability to obtain financing, but, at the same point, will also trigger own decisions about the geographical location of establishments or the selection of suppliers. Second, in the face of increasing climate change, the impact of storm risk is expected to risk even further, making it probable that the premium will persist in the long run.[4] Third, while insurance coverage could take pressure off the cost of equity, the price of natural catastrophe insurance is already high and can be expected to grow even further as climate change deforms the distribution of insured losses. Notwithstanding new solutions for the transfer of natural disaster risk, such as insurance-linked securities (ILS),[5] protection gaps are therefore likely to become wider instead of narrower. Fourth, we document how natural disaster risk is linked to asset returns, implying that insurance and capital markets are converging much faster than previously thought.

The remainder of the paper is organized as follows. In Section 2, we review the related literature. Section 3 lays the theoretical foundations in form of an extended consumption-based asset pricing model with heterogeneous agents subject to idiosyncratic consumption shocks. Section 4 introduces the data. Section 5 empirically shows that a stock's $LSLG$ beta is priced in the cross-section of domestic returns. In Section 6, we provide additional tests to rationalize the emergence and magnitude of the storm risk premium. Section 7 concludes.

[4]See Trapp et al. (2007) for an extrapolation of thunderstorm risk throughout the 21st century.

[5]ILS allow for a direct transfer of disaster risk to capital markets (see, e.g., Braun, 2016)

2. Related Literature

Our work primarily contributes to the rapidly expanding literature on asset pricing implications of physical climate risk (see Gostlow, 2022; Sun et al., 2021; Hain et al., 2022; Schubert, 2022; Bua et al., 2022; Acharya et al., 2023; Lontzek et al., 2023; Sautner et al., 2023a; Kruttli et al., 2023).[6] The paper closest to ours is Kruttli et al. (2023), who quantify the extent of extreme weather uncertainty faced by firms and analyze the pricing of this uncertainty. More specifically, they focus on changes in implied volatility around hurricane landfalls for stock options of firms with facilities in the disaster area. By evaluating analyst calls, they then identify business interruption and physical damages as main drivers of uncertainty and document that the corresponding idiosyncratic volatility has been priced after Hurricane Sandy in 2012.

Our paper differs from theirs in at least three ways. First, in contrast to Kruttli et al. (2023), we do not focus on idiosyncratic volatility but on the covariation of stock returns with extreme weather risk. Second, instead of hurricanes, our analysis is based on severe convective storms, which are less salient but more frequently occurring.[7] This allows us to estimate individual stocks' betas with regard to storm risk and their asset pricing implications. Third, we offer a different theoretical explanation for the pricing of local extreme weather events that affect subsets of households and firms in the economy. Kruttli et al. (2023) connect uncertainty and expected returns by modifying the model of Merton (1987), which

[6] A related literature looks at the effects of sea level rise on real estate markets (Bernstein et al., 2019; Baldauf et al., 2020; Keys & Mulder, 2020; Murfin & Spiegel, 2020; Bakkensen & Barrage, 2021; Gourevitch et al., 2023).

[7] Kruttli et al. (2023) identify 37 events in the time period from 1996 to 2019, whereas our data comprises ten-thousands of convective storm events.

assumes that investors are underdiversified. We extend the consumption-based framework with heterogeneous agents of Constantinides & Duffie (1996) to show under which conditions idiosyncratic weather shocks may produce a risk premium.

We also relate to the broader climate finance literature, which has previously concentrated on carbon risk (see Ilhan et al., 2020; Bolton & Kacperczyk, 2021a,b), transition risk (see Dietz et al., 2016), hedging (see Baker et al., 2022; Andersson et al., 2016; Engle et al., 2020), the importance of climate risks for institutional investors (see Roth Tran, 2019; Krueger et al., 2020), the measuring of climate risk (see Sautner et al., 2023b), and firms' access to capital (see Schüwer et al., 2019). We add evidence that investors care about severe convective storms as a specific type of climate-related event when determining firms' cost of equity.

Given our theoretical framework, this paper also speaks to the strand of the asset pricing literature that incorporates rare disasters into consumption-based models to explain the historical equity premium (Rietz, 1988; Barro, 2006; Berkman et al., 2011; Gabaix, 2012; Wachter, 2013). While these studies focus on political and economic events, such as wars and recessions, anecdotal evidence indicates that extreme natural disasters may lead to severe economic contractions as well.[8] Due to their extraordinarily long recurrence periods, however, the impact of mega catastrophes on asset prices is hard to measure empirically. We focus on recurring thunderstorm risk that may not be extreme enough to affect consumption growth of the representative investor, but can increase consumption

[8]For instance, the San Francisco earthquake in 1906 reduced U.S. GNP by 1.5−1.8 percentage points and contributed to the financial crisis and the stock market crash in 1907 (Odell & Weidenmier, 2004).

heterogeneity in the economy.

Since the most extreme form of storms are hurricanes, we also add to the recent literature on the corporate finance implications of hurricane risk. Contributions in this strand show how hurricanes impact firms through management reactions (see Dessaint & Matray, 2017), cash flow shocks (see Brown et al., 2021), reallocation of capital (see Cortés & Strahan, 2017), and credit constraints (see Collier et al., 2020). There are even immediate connections between hurricane risk and stock markets through uncertainty effects on market liquidity, overreactions of fund managers, and fire sales by hurricane-struck investors with spontaneous liquidity needs (see Rehse et al., 2019; Tubaldi, 2021; Alok et al., 2020). We extend this literature by unveiling a link between convective storm exposure and firm value.

Finally, we add to the thriving research stream on the economics of natural disasters. Previous studies in this field have considered the impact of natural disasters on growth (see Strobl, 2011; Cavallo et al., 2013; Felbermayr & Gröschl, 2014), consumption (see Sawada & Shimizutani, 2008; Aladangady et al., 2017), income (see Miljkovic & Miljkovic, 2014), firm sales (see Addoum et al., 2020), and local labor markets (see Belasen & Polachek, 2008; McIntosh, 2008). Other articles focused on post-disaster recovery effects (see Döhrmann et al., 2017; del Valle et al., 2020), major implications of natural catastrophe risk for policymakers (see Michel-Kerjan & Kunreuther, 2011; Pindyck & Wang, 2013; Martin & Pindyck, 2015) as well as the economics of climate change, which will likely magnify future losses from atmospheric natural disasters (see Stern, 2008; Custodio et al., 2021). Our findings enrich this literature with empirical evidence for the relevance of extreme weather risk in financial markets.

3. Theoretical Foundation

Below, we build a theoretical framework rooted in consumption-based asset pricing with heterogeneous agents subject to idiosyncratic consumption shocks (see Mankiw, 1986; Weil, 1992; Heaton & Lucas, 1996; Constantinides & Duffie, 1996; Gomes & Michaelides, 2011). Extreme weather events are a prime example for an aggregate shock that does not spread equally throughout the economy. *Ex ante*, a large fraction of individuals are exposed. *Ex post*, however, the consumption loss is concentrated among a few. Severe convective storms in particular can impact households and businesses in the disaster area through a variety of economic channels such as direct damage to physical assets as well as disruptions of production networks, supply chains, sales activities, and utility lifelines (Hallegatte, 2015; Kruttli et al., 2023).

Apart from investor heterogeneity, we assume incomplete consumption insurance as in Mankiw (1986), implying that there are no contingent-claims markets that allow for full risk sharing among the heterogeneous agents in the economy. This is a reasonable conjecture, because insurance against large-scale natural disaster risk is largely unavailable or unaffordable.[9] Accordingly, empirical evidence rejects the full consumption insurance hypothesis in this context (see, e.g., Sawada & Shimizutani, 2007). With regard to convective storms, wind and extreme precipitation are the major loss drivers (see, e.g., Larsen, 2016;

[9] The reluctance of insurance companies to provide coverage can be attributed to capitalization frictions and nondiversification traps (Jaffee & Russell, 1997; Froot, 2001; Ibragimov et al., 2009). Attempts to solve the problem through alternative risk transfer solutions and public private partnerships have been increasing in recent decades (Cummins, 2006; Cummins & Trainar, 2009). Nevertheless, natural disaster protection gaps remain substantial (Holzheu & Turner, 2018).

Wing et al., 2020). They disrupt transmission and distribution (T&D) lines, overburden sewage systems, and results in widespread flooding of urban agglomerations, thus inflicting serious physical damage and business interruption losses on the economy (Vilier et al., 2014). These losses are generally underinsured. Despite the availability of subsidized coverage from the National Flood Insurance Program (NFIP), e.g., flood insurance take-up rates in the U.S. remain very low (Hu, 2022).[10]

To begin with, consider the model of Constantinides & Duffie (1996). Assume that consumers exhibit homogeneous preferences, but heterogeneous consumption (income) processes that are nonstationary and heteroskedastic.[11] Markets are arbitrage-free and consumption comprises labor income plus investment proceeds. The model's main asset pricing implications are reflected by the following Euler equation (see Constantinides & Duffie, 1996):

$$\mathbb{E}_t[\tilde{R}^e_{t+1}] \;\; = \;\; -\frac{cov_t[\tilde{H}_{t+1}, \tilde{R}^e_{t+1}]}{\mathbb{E}_t[\tilde{H}_{t+1}]}, \tag{1}$$

where $\mathbb{E}_t[\cdot]$ and $cov_t[\cdot]$ are the expectation and covariance conditional on the information set available at time t, $\tilde{R}^e_{t+1}$ represents the stochastic excess return of a risky asset (at time $t+1$) and $\tilde{H}_{t+1}$ denotes the stochastic discount factor (SDF) or pricing kernel (at time $t+1$). With constant relative risk aversion (CRRA) represented by the power utility function over time-t consumption C_t, the pricing

[10] Munich Re, e.g., estimates that only 5% of U.S. homeowners are insured against flood losses.

[11] In both Mankiw (1986) and Constantinides & Duffie (1996), the idiosyncratic income processes are consistent with a given aggregate income process, as, e.g., faced by a representative investor.

kernel $\tilde{H}_{t+1}$ introduced by Constantinides & Duffie (1996) is defined as follows:

$$\tilde{H}_{t+1} = \beta \left(\frac{\tilde{C}_{t+1}}{C_t} \right)^{-\alpha} \exp \left(\frac{\alpha\,(\alpha+1)}{2} \tilde{\gamma}^2_{t+1} \right). \tag{2}$$

Here, α equals the RRA coefficient[12], β is the subjective time-discount factor, and $\tilde{\gamma}^2_{t+1}$ is the (cross-sectional) variance of individual log consumption growth. Abusing terminology, we will refer to $\tilde{\gamma}^2_{t+1}$ as consumption inequality. (1) implies that an asset carries a risk premium, if individuals expect its future excess returns to exhibit a negative covariance with $\tilde{H}_{t+1}$. The second factor in (2) reflects the heterogeneous agents' dislike towards uninsurable idiosyncratic consumption risk. For homogeneous consumers, $\tilde{\gamma}^2_{t+1} = 0$ so that (1) reduces to the Euler equation of the standard representative-investor consumption-based model.

Through (2), the RRA coefficient α enters the covariance in (1), which hampers an empirical estimation of the model. Therefore, we draw on the extended Stein's Lemma introduced by Söderlind (2009) to analytically isolate α:

Assume (a) the joint distribution of $\tilde{x}$ and $\tilde{y}$ is a mixture of n bivariate normal distributions; (b) the mean and variance of $\tilde{y}$ is the same in each of the n components; (c) $h(\tilde{y})$ is a differentiable function such that $\mathbb{E}[|h'(\tilde{y})|] < \infty$. Then, $cov[\tilde{x}, h(\tilde{y})] = \mathbb{E}[h'(\tilde{y})] \cdot cov[\tilde{x}, \tilde{y}]$.

Given the log SDF is Gaussian, we can proceed as follows. Recognizing that

[12]Since $u(C_t) = \frac{C_t^{1-\alpha}}{1-\alpha}$, $\alpha \to 1$ leads to $u(C_t) = \ln(C_t)$. The marginal utility is therefore $u'(C_t) = C_t^{-\alpha}$

$\tilde{x} = \tilde{R}^e_{t+1}$, $\tilde{y} = \ln(\tilde{H}_{t+1})$, and $h(\cdot) = \exp(\cdot)$, we may decompose the covariance $cov_t[\tilde{H}_{t+1}, \tilde{R}^e_{t+1}]$ in (1) as follows:

$$cov_t[\tilde{H}_{t+1}, \tilde{R}^e_{t+1}] = \mathbb{E}_t[\tilde{H}_{t+1}] \cdot cov_t[\tilde{h}_{t+1}, \tilde{R}^e_{t+1}], \tag{3}$$

with $\tilde{h}_{t+1} = \ln(\tilde{H}_{t+1})$. Denoting log consumption growth $\Delta\tilde{c}_{t+1} = \ln(\tilde{C}_{t+1}/C_t)$, we obtain the following expression for the log SDF:

$$\tilde{h}_{t+1} = \ln(\beta) - \alpha\Delta\tilde{c}_{t+1} + \frac{\alpha(\alpha+1)}{2}\tilde{\gamma}^2_{t+1}, \tag{4}$$

which implies

$$cov_t[\tilde{h}_{t+1}, \tilde{R}^e_{t+1}] = -\alpha \cdot cov_t[\Delta\tilde{c}_{t+1}, \tilde{R}^e_{t+1}] + \frac{\alpha(\alpha+1)}{2} \cdot cov_t[\tilde{\gamma}^2_{t+1}, \tilde{R}^e_{t+1}]. \tag{5}$$

The second covariance on the right hand side will be nonzero, if consumption inequality is correlated with the excess return of the risky asset. By means of (3) and (5), we may restate the risk premium (1) as follows:

$$\begin{aligned} \mathbb{E}_t[\tilde{R}^e_{t+1}] &= \rho_t[\Delta\tilde{c}_{t+1}, \tilde{R}^e_{t+1}] \cdot \sigma_t[\Delta\tilde{c}_{t+1}] \cdot \sigma_t[\tilde{R}^e_{t+1}] \cdot \alpha \\ &- \rho_t[\tilde{\gamma}^2_{t+1}, \tilde{R}^e_{t+1}] \cdot \sigma_t[\tilde{\gamma}^2_{t+1}] \cdot \sigma_t[\tilde{R}^e_{t+1}] \cdot \frac{\alpha(\alpha+1)}{2}. \end{aligned} \tag{6}$$

In addition to the variables of the classical representative investor model included in the first summand of (6), we have a second driver of the risk premium, governed by the correlation $\rho_t[\tilde{\gamma}^2_{t+1}, \tilde{R}^e_{t+1}]$ as well as the standard deviations $\sigma_t[\tilde{\gamma}^2_{t+1}]$ and $\sigma_t[\tilde{R}^e_{t+1}]$. Hence, the model predicts a risk premium for assets, whose future excess returns are expected to positively correlate with log consumption growth and negatively correlate with consumption inequality. Assets with these properties tend to suffer when consumption growth is low and when consumption inequality is large. Both characteristics are disfavored by the heterogeneous agents.

Next, we interlace extreme weather risk as a fundamental factor. To this end, let $\Delta\tilde{l}_{t+1} = \ln(\tilde{L}_{t+1}/\tilde{L}_t)$ be log storm loss growth or *LSLG*, with $\tilde{L}_t$ denoting per capita storm losses at time t. We proceed by demeaning and standardizing the key random variables $\Delta\tilde{c}_{t+1}$, $\tilde{\gamma}^2_{t+1}$, and $\Delta\tilde{l}_{t+1}$. This allows us to decompose the correlations in (6) as follows:[13]

$$\begin{aligned}\mathbb{E}_t[\tilde{R}^e_{t+1}] \;&=\; \Big(\rho_t[\Delta\tilde{c}_{t+1}, \Delta\tilde{l}_{t+1}] \cdot \rho_t[\tilde{R}^e_{t+1}, \Delta\tilde{l}_{t+1}] + \mathbb{E}_t[\Delta\tilde{c}^*_{t+1}\tilde{R}^{e*}_{t+1}]\Big) \cdot \alpha \\ &-\; \Big(\rho_t[\tilde{\gamma}^2_{t+1}, \Delta\tilde{l}_{t+1}] \cdot \rho_t[\tilde{R}^e_{t+1}, \Delta\tilde{l}_{t+1}] + \mathbb{E}_t[\Delta\tilde{\gamma}^{*2}_{t+1}\tilde{R}^{e*}_{t+1}]\Big) \cdot \frac{\alpha(\alpha+1)}{2}. \quad (7)\end{aligned}$$

$\tilde{c}^*_{t+1}$, $\tilde{R}^{e*}_{t+1}$ as well as $\Delta\tilde{\gamma}^{*2}_{t+1}$ reflect those components of the random variables $\tilde{c}_{t+1}$, $\tilde{R}^e_{t+1}$ and $\tilde{\gamma}^2_{t+1}$ that are orthogonal to $\Delta\tilde{l}_{t+1}$.[14] Equation (7) predicts a storm risk premium based on expected correlations between macroeconomic fundamentals and *LSLG* ($\rho_t[\Delta\tilde{c}_{t+1}, \Delta\tilde{l}_{t+1}]$, $\rho_t[\tilde{\gamma}^2_{t+1}, \Delta\tilde{l}_{t+1}]$) and the expected correlation between the excess return on a risky asset and *LSLG* ($\rho_t[\tilde{R}^e_{t+1}, \Delta\tilde{l}_{t+1}]$). By the law of iterated expectations, this equation also holds for unconditional moments.

We can now aim for an empirical verification in two steps: For a storm risk premium to arise, we need (i) *LSLG* to be (negatively) correlated with log consumption growth and/or (positively) correlated with consumption inequality and

---

[13] The mathematical derivation underlying the decomposition of $\rho_t[\Delta\tilde{c}_{t+1}, \tilde{R}^e_{t+1}]$ and $\rho_t[\tilde{\gamma}^2_{t+1}, \tilde{R}^e_{t+1}]$ can be found in the Appendix (Section 8). Specifically, we apply Equation (19) with $X = \Delta\tilde{c}_{t+1}$ or $X = \tilde{\gamma}^2_{t+1}$ as well as $Y = \Delta\tilde{l}_{t+1}$ and $Z = \tilde{R}^e_{t+1}$.

[14] Note that (7) does no longer contain standard deviations, because the variables have been standardized.

(ii) *LSLG* to be negatively correlated with excess returns on the risky asset. We expect condition (i) to hold because there is prior empirical evidence that extreme weather events impact consumer spending in affected states (see Auffret, 2003; Aladangady et al., 2017) and that they exacerbate within-country income inequality (see Miljkovic & Miljkovic, 2014; Palagi et al., 2022; Zanocco et al., 2022; Smiley et al., 2022). Income inequality, in turn, is a common measure for consumption inequality (see, e.g., Attanasio & Pistaferri, 2016; Chen & Yang, 2019). Moreover, we expect the stocks of exposed firms to fulfill condition (ii) because, just as households, businesses are known to be underinsured against natural disasters (see, e.g., Kruttli et al., 2023). Reasons are expensive insurance premiums and the shortage of coverage in particularly exposed regions, which can be attributed to nondiversification traps and capitalization frictions (see, e.g., Zanjani, 2002; Ibragimov et al., 2009). Thus, even firms that are prepared to pay high premiums for property and business interruption policies will often be unable to fully insure against extreme weather events. Stocks of exposed firms should thus be sensitive to extreme weather losses.

4. Data

4.1. Storm losses and macroeconomic data

To test the empirical implications of our theory, we merge data from several sources. We estimate $\Delta\tilde{c}$ from per capita U.S. consumption expenditures and $\tilde{\gamma}^2$ as the state-level cross-sectional variance of log income growth. We adjust nominal figures using the Consumer Price Index (CPI) (base year 2009). Both quarterly consumption and income statistics have been obtained from the BEA. Moreover, we estimate $\Delta\tilde{l}$, i.e., *LSLG* based on inflation-adjusted thunderstorm loss data (per capita) from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS is a natural disaster database capturing a large range of perils like thunderstorms, hurricanes, floods, and wildfires. The data encompasses event dates, event locations, property losses, crop losses, as well as injuries and fatalities since 1960. We download the per capita property and crop losses caused by thunderstorms in each month and across all states. Subsequently, we log and difference this time series to obtain monthly *LSLG* (per capita). To match the frequency of the consumption data, we also generate a quarterly series of *LSLG*. Consistent with $\Delta\tilde{c}$ and $\tilde{\gamma}^2$, $\Delta\tilde{l}$ is considered in real terms (2009 US dollars)

Figure 1 shows the yearly number of severe thunderstorms in the U.S. as given by SHELDUS data in combination with the global temperature anomalies in the same time period. Both have been increasing since the 1980s. We run a Chow test and identify a structural change around 1995 (F-statistic: 8.7639, p-value: 0.0005). The average number of yearly disaster events jumped from 4402 for the period from 1960 to 1994 to 6642 between 1995 and 2019. This difference in means between these periods is statistically significant (t-statistic: -5.5318, p-value: 0.0000) and likely attributable to anthropogenic forcing rather than natural cycles (Hoeppe, 2016).[15] We use this insight to guide our empirical analyses in the following section. In particular, the increase in the mean number of events suggests that if severe storm risk is an economic risk factor that drives financial markets, it probably has been since the mid 1990s.

[15] Environments with high levels of convective available potential energy (CAPE) are known to be more conducive to the formation of severe thunderstorms and CAPE increases with climate change (Brooks, 2013).

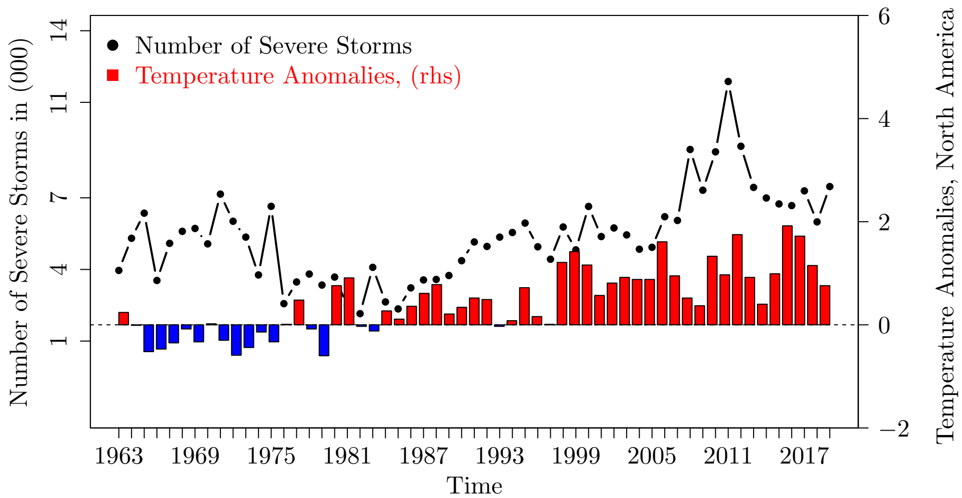


Figure 1: Temperature Anomalies and Number of Severe Thunderstorms

This figure shows the temperature anomalies in North America in °C (right axis) as published by the NOAA National Centers for Environmental information together with the yearly number of severe thunderstorms (left axis) from SHELDUS.

4.2. Stock Market and Accounting Data

In addition to the thunderstorm losses and the macroeconomic data, we obtain monthly returns of all common stocks traded on the NYSE, AMEX, and NASDAQ from June 1, 1964 to December 31, 2019.[16] Those are available in the CRSP/Compustat Merged (CCM) database (share code 10 and 11) that we access through Wharton Return Data Service (WRDS). Following Denis et al. (2002), we split our sample into purely domestic and globally-diversified firms based on their international sales in the Compustat segment data.[17] We consider any firm as

[16]This is the usual time period for empirical asset pricing studies, because an expansion of the CRSP database in August 1962 dramatically increased the number of available stocks (see, e.g., Kelly & Jiang, 2014).

[17]Since 1977, companies in the U.S. must report audited data on foreign segments that comprise more than 10% of consolidated sales, profits or assets.

domestic if it reports at least 90% of sales within U.S. borders. Our focus in the analysis will be on domestic firms since international diversification of sales and assets is a highly plausible remedy against losses from domestic extreme weather events. For each firm, we add headquarter location, CIK numbers, and relevant firm characteristics from the CRSP/Compustat sample. For the period from 1995, our sample comprises 3'626 domestic firms and 288'577 firm-month return observations.

Domestic Firms (N = 3'626)							
01/1995–12/2019	mean	s.d.	skew	kurt	25% quantile	50% quantile	75% quantile
$\beta^{\Delta\tilde{l}}$	0.053	1.125	0.790	26.185	−0.484	0.011	0.552
size	5.392	2.016	0.154	2.676	3.942	5.326	6.579
btm	0.993	2.302	12.502	262.995	0.357	0.647	1.068
mkt beta	1.034	0.765	0.905	5.630	0.524	0.922	1.425
id vola	0.144	0.09	3.252	33.492	0.085	0.123	0.178
coskew	−0.176	0.214	−0.011	4.723	−0.314	−0.181	−0.043
reversal	0.941	16.501	2.773	38.298	−6.624	−0.113	6.698
past ret	10.595	66.093	4.038	49.570	−22.125	1.758	28.438

Table 1: Summary Statistics

This table displays summary statistics for the main variables used in this study (pooled over all stocks and months). The first four columns show the mean, standard deviation, skewness, and kurtosis of the pooled data. The three last columns show the 25%-quantile, 50%-quantile (median), 75%-quantile of each variable. $\beta^{\Delta\tilde{l}}$ is a firm's *LSLG* beta. Size is the natural logarithm of a firm's market capitalization. Book-to-market (btm) ratios are computed in line with Fama & French (1993), who assume that the accounting data for a specific calendar year is not known until the end of June of the subsequent year.[18] Market beta (mkt beta) is estimated by means of a 60-month rolling CAPM-regression on the market factor from Ken French's website. Following Ruenzi et al. (2020), we use standard deviations of the residuals of these regressions as idiosyncratic volatilities (id vola). Coskewness (coskew) of the excess returns with the market factor is also estimated based on a 60-month rolling window. Moreover, we account for short-term reversal (reversal), defined as the stock's return in month t, and stock-level momentum, defined as the return during the 11-month period from month $t-11$ until month $t-1$ (past ret) (Jegadeesh, 1990; Jegadeesh & Titman, 1993, respectively).

Table 1 contains summary statistics of firms' *LSLG* betas ($\beta^{\Delta\tilde{l}}$), and additional firm characteristics. *LSLG* betas are computed based on a 60-month rolling regression of the stocks' excess returns on the Fama & French (1993) three-factor model plus Carhart (1997)'s momentum factor and *LSLG* (see next Section 5.2). Size is the natural logarithm of a firm's monthly market capitalization. Book-to-market ratios are computed in line with Fama & French (1993), who assume that the accounting data for a specific calendar year is not known until the end of June of the subsequent year.[19] Market beta is estimated by means of a 60-month rolling CAPM-regression on the market factor from Ken French's website. Following Ruenzi et al. (2020), we use standard deviations of the residuals of these regressions as a measure of idiosyncratic volatility. Coskewness of the excess returns with the market factor is also estimated based on a 60-month rolling window. Moreover, we account for the past return during the 11-month period from month $t-11$ until $t-1$ (stock-level momentum) and the past one-month return (stock-level reversal) (Jegadeesh & Titman, 1993; Jegadeesh, 1990, respectively). We complement the descriptive statistics in Table 1 with correlations between the firm characteristics, shown in Table 2.

5. Empirical Analysis

5.1. Extreme Weather Risk and Macroeconomic Fundamentals

In line with our theoretical framework, we now investigate the empirical correlations between *LSLG* ($\Delta\tilde{l}$), log consumption growth ($\Delta\tilde{c}$), and consumption inequality ($\tilde{\gamma}^2$). Due to the structural break in our storm and climate data revealed in Section 4, we split the sample in the time period before and after

[19] We exclude firm-months with missing book-to-market estimates.

Domestic Firms (N = 3'626)								
01/1995–12/2019	$\beta^{\Delta\tilde{l}}$	size	btm	mk beta	id vola	coskew	reversal	past ret
$\beta^{\Delta\tilde{l}}$	1	-	-	-	-	-	-	-
size	-0.04	1	-	-	-	-	-	-
btm	0.02	-0.13	1	-	-	-	-	-
mkt beta	0.03	0.07	0	1	-	-	-	-
id vola	0.11	-0.44	0.04	0.33	1	-	-	-
coskew	-0.04	0.01	0.00	-0.09	0.03	1	-	-
reversal	0.00	0.05	0.02	0.01	0.04	0.03	1	-
past return	0.01	0.13	0.05	0.03	0.09	0.04	0.21	1

Table 2: Correlations

This table displays linear correlations between the independent variables used in this study (pooled over all stocks and months). $\beta^{\Delta\tilde{l}}$ is a firm's *LSLG* beta. Size is the natural logarithm of a firm's market capitalization. Book-to-market (btm) ratios are computed in line with Fama & French (1993), who assume that the accounting data for a specific calendar year is not known until the end of June of the subsequent year.[20] Market beta (mkt beta) is estimated by means of a 60-month rolling CAPM-regression on the market factor from Ken French's website. Following Ruenzi et al. (2020), we use standard deviations of the residuals of these regressions as idiosyncratic volatilities (id vola). Coskewness (coskew) of the excess returns with the market factor is also estimated based on a 60-month rolling window. Moreover, we account for short-term reversal (reversal), defined as the stock's return in month t, and stock-level momentum, defined as the stock's return in month t, and stock-level momentum, defined as the return during the 11-month period from month $t-11$ until month $t-1$ (past ret) (Jegadeesh, 1990; Jegadeesh & Titman, 1993, respectively).

1995. Table 3 contains a range of descriptive statistics for the three fundamental variables $\Delta\tilde{l}$, $\Delta\tilde{c}$, and $\tilde{\gamma}^2$ together with the relevant correlations for the periods Q2/1963−Q4/1994 and Q1/1995−Q4/2019.[21] We find log consumption growth to be generally uncorrelated with *LSLG*: $\rho[\Delta\tilde{c}, \Delta\tilde{l}]$ does not significantly differ from zero in any of the two time periods. This is reasonable as only the most extreme natural disasters have loss potentials great enough to affect consumption growth (and thus marginal utility) of the representative agent (Bauer et al., 2013; Braun et al., 2019).[22] However, such events are clearly too rare to drive an empirical correlation over a time horizon of six decades. In contrast, the correlation between *LSLG* and consumption inequality ($\rho[\tilde{\gamma}^2, \Delta\tilde{l}]$) is positive (value of 0.249) and statistically significant at the 5% level for the period from 1995 to 2019. This is consistent with existing empirical evidence for the impact of extreme weather losses on income inequality. Hence, the first necessary condition for a storm risk premium is given from 1995 onwards.

5.2. LSLG Betas and Univariate Sorts

We will now examine the second condition for the storm risk premium, i.e., a negative correlation between excess returns and *LSLG*. First, we convert all returns into excess returns by subtracting the contemporary one-month T-Bill rate. Next, we measure the stocks' storm risk sensitivities by means of *LSLG* betas

[21] Both storm losses and consumption are flow measures. We thus require a timing convention to compute log growth. As suggested by Campbell (2003), we resort to an end-of-period logic, meaning that $\Delta\tilde{l}$ and $\Delta\tilde{c}$ in a specific period are calculated by dividing the level in the current period by the level in the previous period.

[22] A mega-thrust earthquake or a super storm that directly hit a densely populated area of major economic importance could have this effect. The 1906 San Francisco bay earthquake is an example (for details see Odell & Weidenmier, 2004).

Q1/1963–Q4/1994	mean	median	s.d.	min.	max.	$\rho[\cdot, \Delta\tilde{l}]$	p-val.
$\Delta\tilde{l}$	0.009	0.147	3.216	−8.622	10.235	1.000	
$\Delta\tilde{c}$	0.486	0.526	0.906	−3.452	2.268	0.048	0.592
$\tilde{\gamma}^2$	1.812	1.062	1.904	0.184	9.034	0.047	0.602

Q1/1995–Q4/2019	mean	median	s.d.	min.	max.	$\rho[\cdot, \Delta\tilde{l}]$	p-val.
$\Delta\tilde{l}$	−0.017	−0.015	2.679	−5.471	5.453	1.000	
$\Delta\tilde{c}$	0.549	0.559	0.522	−1.554	1.716	−0.039	0.698
$\tilde{\gamma}^2$	0.722	0.389	0.723	0.086	3.834	0.249	0.012**

Table 3: Descriptive Statistics and Correlations for SLG and Macroeconomic Fundamentals

This table shows the mean, median, standard deviation (s.d.), minimum and maximum for the quarterly time series of *LSLG* ($\Delta\tilde{l}$), log consumption growth ($\Delta\tilde{c}$), and income inequality ($\tilde{\gamma}^2$) in the periods Q1/1963–Q4/1994 and Q1/1995–Q4/2019. Moreover, it includes empirical estimates for the linear correlations $\rho[\Delta\tilde{c}, \Delta\tilde{l}]$ and $\rho[\tilde{\gamma}^2, \Delta\tilde{l}]$.

(i.e., a transformed correlations), denoted $\beta_i^{\Delta\tilde{l}}$. The latter reflect the sensitivity of a stock's excess returns with regard to $\Delta\tilde{l}$. We estimate the monthly $LSLG$ betas using the following time series regression over the 60 months prior to the sorting date:

$$R_{i,t}^e = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{HML} HML_t + \beta_i^{SMB} SMB_t + \beta_i^{MOM} MOM_t + \beta_i^{\Delta\tilde{l}} \Delta\tilde{l}_t + \epsilon_{i,t}. \tag{8}$$

$R_{i,t}^e$, MKT_t, HML_t, SMB_t and MOM_t are the monthly excess returns on stock i, the market factor, and the Fama & French (1993) factors as well as the Carhart (1997) momentum factor, reflecting book-to-market, size and momentum anomalies.

Stocks of firms that suffer (benefit) in the wake of severe storm events will exhibit a negative (positive) $\beta_i^{\Delta\tilde{l}}$.[23] To test our second condition for the storm

[23]Concrete examples can be found in Tables 12 of the Appendix.

risk premium, we first sort the monthly cross sections of stocks into value-weighted quintile portfolios based on their $LSLG$ betas in month t.[24] We then evaluate raw and risk-adjusted returns in month $t + 1$. The portfolio with the largest negative (positive) $LSLG$ beta comprises the most (least) risky stocks. Thus, from the perspective of investors, stocks with negative $LSLG$ betas should earn higher excess than stocks with positive $LSLG$ betas.

Table 4 shows the results for the time period 06/1969−12/1994[25] in the upper panel and for the time period 01/1995−12/2019 in the lower panel. We report the portfolio with the highest negative (positive) $LSLG$ betas as portfolio 1 (portfolio 5) at the top (bottom). Economically, portfolio 1 reflects the stocks that are most exposed to extreme weather risk and portfolio 5 acts as an extreme weather risk insurance for investors. The row labeled 1−5 contains the corresponding zero-investment portfolio, which will hereafter refer to as NMP (negative minus positive $LSLG$ beta). Average betas are included in the first column and average excess returns in the second column. The remaining columns indicate the abnormal excess returns (alphas) that remain when regressing the excess return time series of the respective portfolios on the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model and the Carhart (1997) four-factor model.

In line with our theory, we find a significant storm risk effect for domestic firms in the period from 01/1995− 12/2019. The average monthly excess returns exhibit

[24]As is common in the literature, we exclude stocks with the 0.5% lowest market cap in a given month.

[25]The first time period can be explained as follows. The CRSP/Compustat merged data begins in June 1964 and we require 60 months for the estimation of our first $LSLG$ beta.

a clean monotonic decrease from portfolio 1 (1.007%) to portfolio 5 (0.468%). Accordingly, the zero-investment portfolio NMP earned a highly significant average excess return of 0.538% per month (6.5% p.a.). Even after controlling for the established factors in columns four and five, we are left with sizeable and statistically significant abnormal returns.[26] Also consistent with our theoretical considerations, we do not find a storm risk premium for the period 06/1969−12/1994, in which the empirically-estimated correlations between macroeconomic fundamentals and *LSLG* were insignificant (see Table 3). Hence, the rest of our empirical analyses will focus on domestic stocks in the period after 1995.

5.3. Time Series Regressions

We continue by regressing the time series of the NMP portfolio return on a comprehensive battery of major factors from the asset pricing literature. The respective data has been obtained directly from author webpages. We present the results of these analyses in Table 5. Each model in columns one to eight combines the market (MKT), small-minus-big (SMB), and high-minus-low (HML) factors from Fama & French (1993) plus the momentum factor (MOM) from Carhart (1997) with one additional factor. The extensions include the lower tail dependence (LTD) factor from Chabi-Yo et al. (2018), the Pástor & Stambaugh (2003) traded liquidity risk factor (PS), the Sadka (2006) liquidity factor (SAD), the Baker et al. (2022) sentiment index, orthogonalized with respect to a set of macroeconomic conditions (SENT), the Jurek & Stafford (2015) downside market risk factor (JS), the WTI oil index (WTI), and the Frazzini & Pedersen (2014) betting-against-beta

[26]The order of magnitude is comparable to existing asset pricing factors. Chabi-Yo et al. (2018), e.g., find a stock market crash-sensitivity premium of 4.32% p.a. for the period from January 1963 to December 2012.

	Domestic Firms (N = 3'192)				
06/1969–12/1994	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−0.631	+0.306%	−0.071%	−0.146%	−0.139%
2	−0.229	+0.351%	+0.037%	−0.109%	−0.158%
3	−0.005	+0.398%	+0.117%	−0.059%	−0.077%
4	+0.222	+0.459%	+0.165%	+0.040%	+0.004%
Portfolio 5	+0.656	+0.431%	+0.055%	−0.019%	−0.045%
NMP (1−5)		−0.125%	−0.126%	−0.044%	−0.095%
t-value		(−0.718)	(−0.093)	(−0.266)	(−0.564)

	Domestic Firms (N = 3'626)				
01/1995–12/2019	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−0.991	+1.007%	+0.292%	+0.261%	+0.179%
2	−0.357	+0.739%	+0.212%	+0.144%	+0.092%
3	−0.011	+0.729%	+0.199%	+0.126%	+0.132%
4	+0.405	+0.692%	+0.063%	−0.015%	−0.032%
Portfolio 5	+1.212	+0.468%	−0.400%	−0.394%	−0.344%
NMP (1−5)		+0.538%**	+0.692%***	+0.655%***	+0.526**
t-value		(2.086)	(2.822)	(2.814)	(2.297)

Table 4: Portfolio Sorts for Domestic Firms

This table shows out-of-sample portfolio sorts between *LSLG* betas in month t and future returns and alphas in month $t+1$ for domestic firms in the time periods June 1969 to December 1994 (upper part) and January 1995 to December 2019 (lower part). N denotes the overall number of firms in each sample (the monthly cross sections vary in size). All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5% lowest market capitalisation in a given month. The portfolio with the highest negative (positive) *LSLG* betas is reported at the top (bottom). The row labeled NMP (1−5) contains the difference between the top and bottom quintiles. Average betas are included in the first and average excess returns in the second column. The remaining columns indicate the alphas that remain when regressing the excess return time series of the respective portfolios on the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model (FF3), and the Carhart (1997) four-factor model. t-statistics are shown in parentheses and were computed using Newey & West (1987) standard errors with 4 monthly lags. ***, ** and * indicate significance at the one, five, and ten % levels.

Domestic Firms (January 1995 to December 2019)										
NMP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1 MKT	−0.079	−0.062	−0.056	−0.082	−0.036	−0.065	−0.079	−0.092	−0.159*	−0.06
1 SMB	−0.199	−0.279	−0.186	−0.265**	−0.268**	−0.300	−0.198	−0.208	−0.178	−0.048
1 HML	0.222**	0.185**	0.263**	0.246**	0.230**	0.209**	0.263**	0.303**	0.189	0.044
1 MOM	0.173***	0.180***	0.179***	0.185***	0.189***	0.186***	0.173***	0.191**		
2 LTD		−0.051								
3 PS			−0.13							
4 SAD				−2.813						
5 SENT					0.231					
6 JS						1.579				
7 WTI							−0.503			
8 BAB								−0.074		
9 REVS									0.044	
9 REVL									−0.009	
10 RMW										0.400***
10 CMA										0.041
alpha	0.526**	0.697**	0.568***	0.689**	0.633**	0.779***	0.529***	0.585**	0.653***	0.454*
t-value	(2.297)	(2.429)	(2.456)	(2.077)	(1.954)	(2.748)	(2.318)	(2.253)	(2.850)	(1.842)
R^2_{adj}	0.099	0.113	0.109	0.119	0.111	0.116	0.099	0.102	0.069	0.099
sample period	(1995-2019)	(1995-2012)	(1995-2019)	(1995-2019)	(2006-2010)	(1996-2012)	(1995-2019)	(1995-2019)	(1995-2019)	(1995-2019)

Table 5: Time Series Regressions of PMN (Value Weighted) on Established Factors

This table shows the results for ten time series regressions of NMP (value-weighted) on established factors. The sample period is January 1995 to December 2019. All t-statistics are based on Newey & West (1987) standard errors with 4 monthly lags. To save space, we report the t-statistics for the abnormal returns (alphas), but not for the regression coefficients. ***, ** and * indicate significance at the one, five, and ten % levels. Model (1) contains the market factor (MKT), consisting of all CRSP stocks, together with SMB and HML (Fama & French, 1993) as well as MOM (Carhart, 1997). The subsequent models (2) through (8) enrich model (1) with: lower tail dependence (LTD) from Chabi-Yo et al. (2018), the Pástor & Stambaugh (2003) liquidity risk factor (PS), Sadka (2006) liquidity factor (SAD), Baker et al. (2022) sentiment index (SENT), the Jurek & Stafford (2015) downside market risk factor (JS), the WTI oil index (WTI), and the Frazzini & Pedersen (2014) betting-against-beta factor (BAB). In models (9) and (10), we replace the Carhart (1997) momentum factor (MOM) with the Fama-French short-term and long-term reversal factors (REVS, REVL), as well as the investment and profitability factors of Fama & French (2015) (CMA, RMW), respectively.

factor (BAB). Furthermore, in models nine and ten, we replace MOM with the Fama-French short-term and long-term reversal factors (REVS, REVL), as well as the investment and profitability factors of Fama & French (2015) (CMA, RMW). In all ten cases, we are left with a statistically significant and economically large positive abnormal excess return of at least 0.454% per month (5.4% p.a.).

5.4. Fama & MacBeth (1973) Regressions

Next, we provide multivariate evidence of a storm risk premium in the form of value-weighted Fama & MacBeth (1973) regressions.[27] Specifically, for each month t in the time series, we run a cross-sectional regression of the excess return realized in the subsequent month $t+1$ on the *LSLG* beta and a set of firm-specific variables measured in month t. The firm characteristics are the ones summarized in Table 1. Consistent with our previous findings, the time period under consideration is 01/1995−12/2019.

Table 6 presents the time-series averages of the monthly cross-sectional regression coefficients together with Newey & West (1987) robust standard errors and significance levels. The coefficient for the *LSLG* beta stays statistically significant negative throughout. In economic terms, based on the last column in Table 6, a standard deviation decrease in the *LSLG* beta increases future returns by 0.152 percentage points. This confirms our sorting results: a (domestic) firm's storm risk exposure has a statistically significant impact on the excess return of its stock in the next month. Stocks with negative *LSLG* betas earn higher future excess

[27] This methodology follows Ang & Chen (2006), who use the firms' market capitalizations at the beginning of each period for the weighting in cross-sectional weighted least squares (WLS) regressions.

returns than those with positive *LSLG* betas.[28]

Domestic Firms (January 1995 to December 2019)						
	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$
$\beta^{\Delta\tilde{l}}$	−0.189**	−0.183**	−0.171*	−0.172*	−0.169*	−0.152*
	(−1.923)	(−1.907)	(−1.836)	(−1.842)	(−1.891)	(−1.824)
size	−0.010	−0.031	−0.032	−0.028	−0.031	−0.051
	(−0.206)	(−0.579)	(−0.593)	(−0.529)	(−0.593)	(−1.011)
mkt beta	−0.003	0.078	0.009	−0.043	−0.039	−0.081
	(−0.012)	(0.435)	(0.041)	(−0.196)	(−0.166)	(−0.359)
idiosyncratic vol		−0.018	−0.016	−0.015	−0.018	−0.027
		(−0.866)	(−0.807)	(−0.03)	(−0.839)	(−0.917)
coskewness			−0.279	−0.346	−0.286	−0.296
			(−1.002)	(−1.286)	(−1.016)	(−1.161)
book-to-market				−0.099	−0.081	−0.093
				(−1.014)	(−0.851)	(−0.987)
past return					−0.022**	−0.021***
					(−3.022)	(−2.915)
reversal						0.286
						(1.004)
alpha	0.774	1.056**	1.065**	1.113**	1.163***	0.901***
	(1.684)	(2.032)	(2.033)	(2.104)	(2.246)	(2.863)

Table 6: Fama & MacBeth (1973) Regressions with Storms Betas and Firm Characteristics

This table presents the results of multivariate value-weighted Fama & MacBeth (1973) regressions of excess returns in month t+1 on a set of firm characteristics measured in month t. The latter are *LSLG* beta ($\beta^{\Delta\tilde{l}}$), size (log of market capitalization), market beta (mkt beta), idiosyncratic excess return volatility (idiosyncratic vol), coskewness of the stock's excess returns with the market's excess returns (coskewness), book-to-market ratio (book-to-market), the excess return between $t-11$ and $t-1$ (past return), and the return between $t-1$ and t return (reversal). The t-statistics in parentheses were computed using Newey & West (1987) standard errors with 6 monthly lags. ***, ** and * indicate significance at the one, five, and ten % levels.

[28]Note that in Table 6 the coefficient estimates on book-to-market, past returns, and reversal are in contrast to most existing empirical asset pricing studies. We can show – in unreported tests – that this is due to our specific sample selection of domestic firms in the relatively short period from 1995 to 2019.

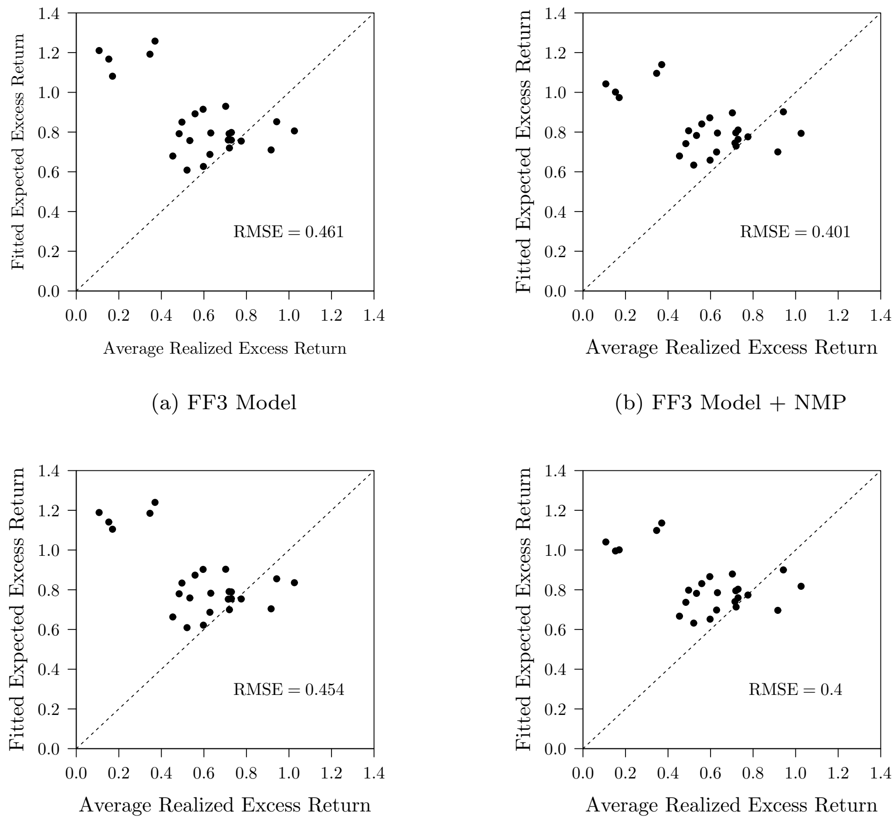
5.5. The Cross Section of Expected Excess Returns

We consider the effect of NMP on 25 test portfolios sorted by size and momentum, which we download from Ken French's website. In Figure 2, we have plotted the model-predicted expected excess returns (vertical axis) against the average realized excess returns (horizontal axis) for the relevant time period from January 1995 to December 2019. Test portfolios for which the models' pricing errors are small closely align along the 45-degree line. We find that adding NMP to the Fama & French (1993) three-factor model and to the Carhart (1997) four-factor model reduces pricing errors in the cross section of test portfolios. This can be determined visually by comparing the fit of both baseline specifications shown in subfigures (a) and (c) to the same models extended with NMP in subfigures (b) and (d). It can also be determined statistically through a decrease in the root mean squared errors (RMSE) from 0.461 in (a) to 0.401 in (b) and from 0.454 in (c) to 0.400 in (d). A Diebold-Mariano test confirms that these reductions are statistically significant (p-values: 0.009 and 0.010). Hence, NMP carries pricing information which is not included in MKT, HML, SMB, and MOM.

5.6. Robustness

We conclude this section with a battery of robustness tests. Specifically, we investigate whether our results hold when we extend the rolling regression window for the *LSLG* betas, when we vary the sample period, when we concentrate on the 50% largest domestic firms, and when we sort on *LSLG* correlations instead of *LSLG* betas.

In Table 7, we consider the sample period from 01/1990 to 12/2019, thus begin-



(a) FF3 Model

(b) FF3 Model + NMP

(c) FF3 Model + MOM

(d) FF3 Model + MOM + NMP

Figure 2: NMP and the Cross Section of Expected Excess Returns

In this figure, the model-predicted expected excess returns (vertical axis) for 25 test portfolios sorted by size and momentum are plotted against the corresponding average realized excess returns (horizontal axis). Subfigures (a) and (c) show the Fama & French (1993) three-factor (FF3) model (MKT, HML, SMB) and its extension with the Carhart (1997) momentum factor (MOM). Subfigures (b) and (d) show both models extended by NMP. The sample period is January 1995 to December 2019. The smallest pricing errors can be found along the dashed 45-degree line. All four subfigures contain the RMSE achieved by the respective models.

ning five years earlier than in our main analyses. This modification does not affect our main findings. The storm risk premium stays statistically and substantively significant. Note that the different sample period inable 7 requires us to return to the first necessary condition for the storm risk premium, i.e., $\rho_t[\tilde{\gamma}^2_{t+1}, \Delta\tilde{l}_{t+1}] > 0$ as well. In the period 01/1990−12/2019, this correlation between $LSLG$ and income inequality amounts to 0.318 and is significant at the 1% level (p.value = 0.0003).

We continue with the robustness tests reported in Table 8. Panel a) shows the results for a modified sorting algorithm. In each month t, we first split the sample in two parts: Domestic firms with the 50% largest and the firms with the 50% smallest market capitalizations. We then exclusively perform the sorting on the first subsample (i.e., the largest firms). We find that our results remain stable and are not friven by illiquidity effects or trading frictions. Panel b), in contrast, shows the results if we sort the undivided sample in the time period 01/1990 to 12/2019 on $LSLG$ correlations instead of $LSLG$ betas (as postulated by our theory). Again, our results of a significant storm risk premium are robust to this alternative specification.

Alternative Time Period, Subsample 1990−2019					
	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−0.825	+0.835%	+0.335%	+0.267%	+0.239%
2	−0.298	+0.625%	+0.185%	+0.099%	+0.036%
3	−0.001	+0.618%	+0.189%	+0.100%	+0.106%
4	+0.337	+0.591%	+0.035%	−0.054%	−0.006%
Portfolio 5	+1.080	+0.389%	−0.445%	−0.457%	−0.416%
NMP (1−5)		+0.446%**	+0.569%***	+0.536%***	+0.414%**
t-value		(2.055)	(2.753)	(2.718)	(2.112)

Table 7: Robustness Test I (Time Period for *LSLG* Betas)

This table shows the univariate sorting results for the subsample from 01/1990 to 12/2019. All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5% lowest market capitalisation in a given month. The portfolio with the highest negative (positive) *LSLG* betas is reported at the top (bottom). The row labeled NMP (1−5) contains the difference between the top and bottom quintiles. Average betas are included in the first and average excess returns in the second column. The remaining columns indicate the alphas that remain when regressing the excess return time series of the respective portfolios on the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model (FF3), and the Carhart (1997) four-factor model. t-statistics are shown in parentheses and were computed using Newey & West (1987) standard errors with 4 monthly lags. ***, ** and * indicate significance at the one, five, and ten % levels.

Panel a) 50% Largest Domestic Firms

	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−0.849	+1.045%	+0.342%	+0.307%	+0.219%
2	−0.324	+0.754%	+0.228%	+0.158%	+0.099%
3	−0.003	+0.690%	+0.171%	+0.099%	+0.098%
4	+0.301	+0.665%	+0.075%	−0.008%	−0.004%
Portfolio 5	+1.000	+0.544%	−0.265%	−0.289%	−0.238%
NMP (1−5)		+0.501%**	+0.608%***	+0.596%**	+0.462%**
t-value		(2.152)	(2.638)	(2.575)	(1.989)

Panel b) Correlation between Excess Returns and *LSLG*

	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−0.155	+0.888%	+0.379%	+0.314%	+0.255%
2	−0.053	+0.702%	+0.075%	+0.023%	+0.005%
3	+0.014	+0.669%	+0.039%	−0.009%	−0.015%
4	+0.081	+0.660%	−0.044%	−0.111%	−0.068%
Portfolio 5	+0.178	+0.525%	−0.176%	−0.213%	−0.230%
NMP (1−5)		+0.363%*	+0.555%***	+0.527%***	+0.493%**
t-value		(1.805)	(2.765)	(2.636)	(2.312)

Table 8: Robustness Tests II (Firm Size and *LSLG* Correlation)

This table shows the out-of-sample portfolio sorts for domestic firms in the time period between January 1995 and December 2019. In panel a), the sorting is conducted among the 50% largest firms in each month, where size is reflected by market capitalization. Panel b) shows the results when firms are sorted on correlation between their excess returns and *LSLG* instead of *LSLG* betas. All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5% lowest market capitalisation in a given month. The portfolio with the highest negative (positive) *LSLG* betas is reported at the top (bottom). The row labeled NMP (1−5) contains the difference between the top and bottom quintiles. Average betas are included in the first and average excess returns in the second column. The remaining columns indicate the alphas that remain when regressing the excess return time series of the respective portfolios on the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model (FF3), and the Carhart (1997) four-factor model. t-statistics are shown in parentheses and were computed using Newey & West (1987) standard errors with 4 monthly lags. ***, ** and * indicate significance at the one, five, and ten % levels.

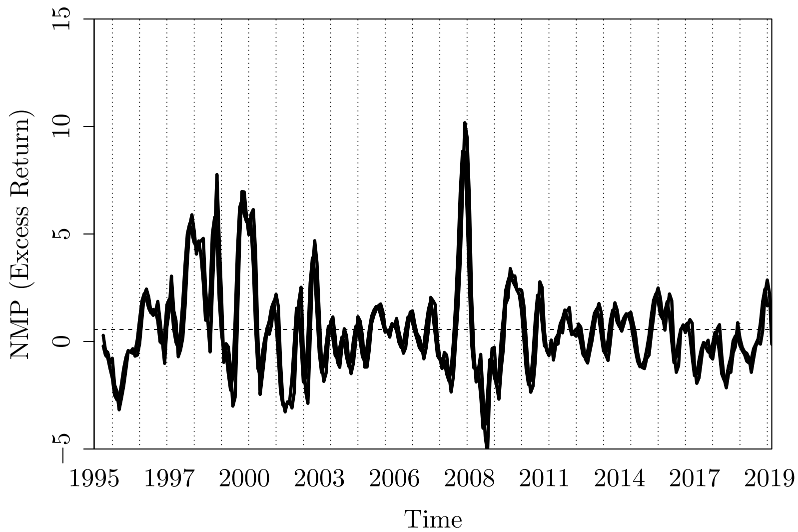
6. Additional Empirical Tests

6.1. Seasonality of the Storm Risk Premium

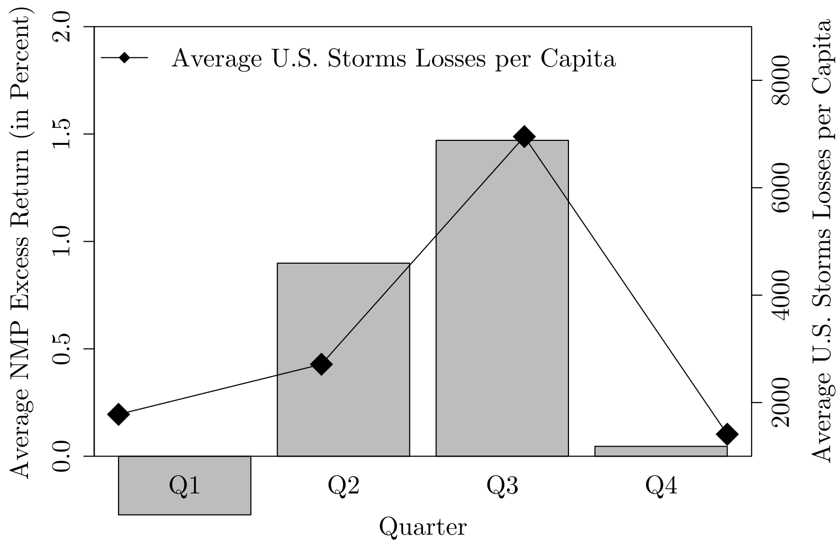
In the next few sections, we want to shed some more light on the properties of the storm risk premium. We begin with seasonality. Thunderstorm risk in the U.S. follows a clear intra-year pattern that can be exploited for identification. It is present from April to October, peaking in the third quarter (see, e.g., Trapp et al., 2007). Outside the season, it is negligible. The time series patterns of NMP can be deduced from Figure 3. In subfigure (a), we see that positive returns regularly occur in the third quarter (vertical dashed lines). This is confirmed by Subfigure (b), in which we plot the average real U.S. thunderstorm losses per capita (based on SHELDUS) during our sample period Q1/1995-Q4/2019 together with the average excess returns of NMP in each quarter. Evidently the intra-year patterns align: average excess returns are highest in Q3, when the underlying extreme weather risk is at its maximum.

We further examine this observation by way of a time series regression of the monthly NMP excess returns on dummy variables for Q2, Q3 and Q4 (Q1 forms the base category), in which we additionally control for differences in the annual market environment via year fixed effects (FE). Panel a) of Table 9) contains the results and uses standard errors which are heteroskedasticity and autocorrelation consistent (HAC). The significant positive coefficient for the third quarter provides a statistical confirmation of our visual findings from Figure 3. The highest excess returns in the NMP return time-series occur at the peak of the thunderstorm season.

In addition, to the time series regression, we fit an ARIMA(1,0,1)$(1,0,0)_{12}$ to the monthly NMP time series and report the results in Panel b) of Table 9. All three ARIMA coefficients are statistically significant. The significant coefficient for the first-order seasonal autoregressive process SAR(1) at period 12 provides further conclusive evidence for an annually repeating pattern. We thus conclude that NMP adheres to the same intra-year seasonality as the underlying thunderstorm risk itself. In other words, investors holding stocks with high *LSLG* betas are compensated with the storm risk premium when the firms are most likely to suffer from an extreme weather event.



(a) NMP Time Series



(b) Average Excess Returns and Thunderstorm Losses by Quarter

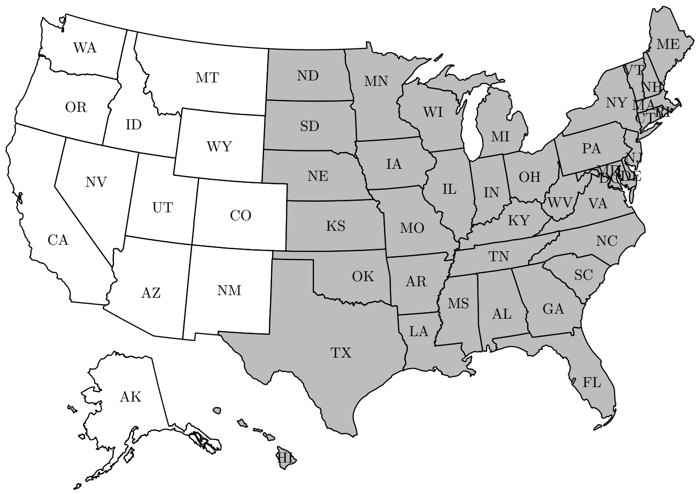
Figure 3: Time Series Patterns of the Zero-Investment Portfolio NMP

The subfigures show: a) the time series of quarterly excess returns (in %) on the zero-investment portfolio NMP (dotted lines indicate Q3) and b) the average excess returns of NMP (in percent) in combination with the average historical per capita U.S. thunderstorm losses by quarter. The sample period is Q1/1995-Q4/2019.

Panel a) TS Regression				**Panel b) SARIMA (NMP)**			
	coeff.	p-val. (NW)	sig.		coeff.	p-val. (NW)	sig.
Intercept	-1.897	0.278					
Q2	1.193	0.209		AR(1)	-0.778	0.042	**
Q3	1.765	0.006	***	MA(1)	0.798	0.029	**
Q4	0.341	0.674		SAR(1)	0.129	0.028	**
df	271			df	296		
Year FE	Yes			AIC	5.883		
BP	50.098	0.004	***	BIC	5.932		
LB(12)	11.733	0.002	***	LB(12)	14.645	0.261	

Table 9: Time Series Analysis of the Zero-Investment Portfolio NMP

In Panel a), we report the coefficients (including intercept), p-values, significance levels and degrees of freedom (df) for a time series (TS) regression of the monthly NMP series on dummy variables for the second, third and fourth quarter (first quarter forms the base category). We control for different annual regimes through year fixed effects (FE). In line with the significant Breusch-Pagan (BP) and Ljung-Box (LB) (lag of 12) tests, all standard errors are heteroskedasticity and autocorrelation consistent (HAC). Panel b) contains the coefficient estimates for an ARIMA$(1,0,1)(1,0,0)_{12}$ model fit to the monthly NMP series. The significant first-order seasonal autoregressive component SAR(1) at the twelfth period indicates an annually repeating pattern in the NMP series. The sample period is January 1995 to December 2019. ***, ** and * indicate significance at the one, five, and ten percent levels.



(a) NOAA Thunderstorm Risk Map

Figure 4: Geographic Thunderstorm Exposure

This figure shows states for which an annual average of at least 10 days with severe storm occurrences was reported between 2003 and 2012. Data is from the National Oceanic and Atmospheric Association (NOAA).

6.2. Dependence on Extreme Weather Exposure

Next, we split our sample of domestic firms based on historical event occurrences as a proxy for geographic exposure. To this end, we focus on states for which the National Oceanic and Atmospheric Association (NOAA) reports an annual average of at least ten severe thunderstorm wind days in the period from 2003 to 2012.[29] The resulting exposure pattern is shown in Figure 4. It is very distinct and implies an East-West split of the U.S. approximately in the middle of the country. Firms with headquarters located in the grey-shaded states are deemed geographically exposed, be it through physical assets that are located inside the hazard area or through a deeper layer of economic linkages. Upon repeating the univari-

[29]The original NOAA map is available under https://www.spc.noaa.gov/wcm/.

ate sorting on *LSLG* betas for the two subsamples of geographically-exposed and geographically-unexposed firms, we expect to see the storm risk premium only for the former. Our results confirm this conjecture. The average excess return of the NMP portfolio (1−5) in the subsample of geographically-exposed firms is reported in Panel a) of Table 10 and amounts to 0.749 percent per month (9.0 percent p.a.).[30]

6.3. The Role of Salience

We also explore the role of salience with regard to the storm risk premium. Following Cohen et al. (2020), we download all 10-K, 10-K405 and 10-KSB filings from the SEC's EDGAR website, spanning the time period from 2000 to 2019, and match them with the CRSP/Compustat data. We then perform a textual analysis on the financial statements, using the keywords "severe storm", "storms", or "thunderstorm" (both lowercase and capitalized). We define salient firms as those that mention these keywords at least once in their financial statements of the five years before the sorting date. Due to the limited availability of the financial reports from EDGAR and our five-year rolling regression window for the *LSLG* betas, the sample period for this analysis reduces to the time span between January 2005 and December 2019. Moreover, the number of stocks shrinks to 3'548 because it was not possible to match the CRSP/Compustat data with EDGAR in all cases. In return, however, we are able to dynamically split the cross section into a subsample of "salient" and "non-salient" firms in each month and sort on *LSLG* betas in each of the two subsamples. Depending on their mentioning or

[30]Note that the number of firms in Table 10 does not sum up to our overall sample size for domestic firms (3'626). The reason is that some firms lack headquarter information and can thus not be included in this analysis.

Panel a) Geographically-Exposed Firms (N = 2'693)					
	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−0.945	+1.091%	−0.514%	−0.518%	−0.476%
2	−0.351	+0.697%	−0.086%	−0.076%	−0.077%
3	−0.006	+0.690%	+0.088%	+0.019%	+0.019%
4	+0.391	+0.699%	+0.221%	+0.134%	+0.134%
Portfolio 5	+1.118	+0.342%	+0.492%	+0.344%	+0.345%
NMP (1−5)		+0.749%***	+0.885%***	+0.823%***	+0.726%***
t-value		(2.693)	(3.182)	(3.141)	(2.675)

Panel b) Geographically-Unexposed Firms (N = 851)					
	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−1.144	+0.895%	+0.074%	−0.058%	−0.031%
2	−0.407	+1.146%	+0.331%	+0.002%	+0.329%
3	+0.005	+0.487%	−0.213%	+0.076%	−0.233%
4	+0.445	+1.090%	+0.333%	+0.069%	+0.396%
Portfolio 5	+1.485	+0.836%	−0.100%	−0.006%	0.030%
NMP (1−5)		+0.058%	+0.483%	+0.174%	−0.063%
t-value		(0.137)	(0.433)	(1.189)	(0.423)

Table 10: Portfolio Sorts for Geographically-Exposed and Geographically-Unexposed Firms

This table shows the out-of-sample portfolio sorts for geographically-exposed (upper part) and geographically-unexposed firms (lower part) in the time period between January 1995 to December 2019. The sample split is based on headquarter locations in combination with the geographic storm risk map published by NOAA (see Figure 4). N denotes the overall number of firms in each sample (the monthly cross sections vary in size). All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5% lowest market capitalisation in a given month. The portfolio with the highest negative (positive) $LSLG$ betas is reported at the top (bottom). The row labeled NMP (1−5) contains the difference between the top and bottom quintiles. Average betas are included in the first and average excess returns in the second column. The remaining columns indicate the alphas that remain when regressing the excess return time series of the respective portfolios on the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model (FF3), and the Carhart (1997) four-factor model. t-statistics are shown in parentheses and were computed using Newey & West (1987) standard errors with 4 monthly lags. ***, ** and * indicate significance at the one, five, and ten % levels.

non-mentioning of severe storms, firms can end up in both the salient and the non-salient subsample over time.

Table 11 contains the results of this analysis. We document a storm risk premium for the salient firms in Panel a). More specifically, the average excess return of the NMP portfolio (1−5) in the subsample of salient firms is statistically significant and equals 0.557% per month (6.7% p.a.). The placebo test for non-salient firms in Panel b), on the other hand, does not show a significant effect. Nevertheless, non-salient firms turn out to be sensitive to *LSLG*. However, investors' awareness of their extreme weather exposure seems to be too low for a significant risk premium to arise. Therefore salience, as reflected by the explicit mentioning of exposure in firm announcements, can be considered an additional requirement for the storm risk premium.

6.4. Industry Patterns

In a last step, we investigate whether the storm risk premium is dependent on the industry sector of a firm. To this end, we break down the subsample of salient firms. Figure 5 shows the percentage of salient firms among the total firms in NAIC industry sectors. Industry sectors not shown in the bar chart do not contain any salient firms. We derive at least two insights from this analysis.

First, Figure 5 suggests that our results for the storm risk premium are not predominantly driven by a single industry sector. The fact that the storm risk premium arises across a broad set of industry sectors indicates the relevance of exposure rather than business model. Second, four industry sectors particularly stand out, with more than 70% of the respective firms being salient: utilities, mining, transportation, and construction (see black bars in Figure 5). The same

Panel a) Salient Firms (N = 1'459)

	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−1.003	+1.124%	−0.514%	−0.518%	−0.476%
2	−0.315	+0.549%	−0.086%	−0.076%	−0.077%
3	−0.025	+0.680%	+0.088%	+0.019%	+0.019%
4	+0.347	+0.703%	+0.221%	+0.134%	+0.134%
Portfolio 5	+1.086	+0.568%	+0.492%	+0.344%	+0.345%
NMP (1−5)		+0.557%**	+0.743%***	+0.831%***	+0.805%***
t-value		(2.026)	(3.249)	(3.641)	(3.482)

Panel b) Non-salient Firms (N = 2'089)

	$\beta^{\Delta\tilde{l}}$	Return	CAPM-α	FF3-α	Carhart-α
Portfolio 1	−1.037	+0.810%	−0.088%	−0.058%	−0.025%
2	−0.376	+1.029%	+0.006%	+0.002%	+0.002%
3	+0.008	+0.724%	+0.055%	+0.076%	+0.076%
4	+0.417	+0.732%	+0.029%	+0.069%	+0.071%
Portfolio 5	+1.291	+0.603%	−0.089%	−0.006%	−0.003%
NMP (1−5)		0.207%	+0.277%	+0.356%	+0.337%
t-value		(0.578)	(0.326)	(0.989)	(0.927)

Table 11: Dynamic Portfolio Sorts for Storms and No-Storms Firms

This table shows the out-of-sample portfolio sorts for salient (upper part) and non-salient firms (lower part) in the time period between January 2005 and December 2019. The sample split is based on a textual analysis of financial statements. Salient firms are those that mention the keywords "severe storm", "storms", or "thunderstorm" at least once in their financial statements of the five years before the sorting date. N denotes the overall number of firms in each sample (the monthly cross sections vary in size). All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5 percent lowest market capitalisation in a given month. The portfolio with the highest negative (positive) *LSLG* betas is reported at the top (bottom). The row labeled NMP (1−5) contains the difference between the top and bottom quintiles. Average betas are included in the first and average excess returns in the second column. The remaining columns indicate the alphas that remain when regressing the excess return time series of the respective portfolios on the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model (FF3), and the Carhart (1997) four-factor model. t-statistics are shown in parentheses and were computed using Newey & West (1987) standard errors with 4 monthly lags. ***, ** and * indicate significance at the one, five, and ten % levels.

sectors are highlighted in the recent study of Kruttli et al. (2023) for hurricane risk. Each case is also highly plausible in the context of severe thunderstorm risk. As mentioned in Section 3, utility firms can suffer from disruptions of T&D lines that result in revenue losses due to power outages as well as costly repairs. In addition, mining companies are inherently tied to the location of natural resources, limiting their flexibility in choosing operational locations to evade storm-risky areas (Kruttli et al., 2023). Transportation firms, may e.g., suffer from service interruptions due to extreme weather and from damaged infrastructure such as roads, bridges, airports and rail tracks. Finally, in contrast to the aforementioned industry sectors, construction companies may benefit from reconstruction efforts after the disaster when there is an immediate need to rebuild infrastructure, homes, and other structures. Table 12 in the appendix offers examples from annual 10-K reports illustrating how companies from the aforementioned four industries have been impacted by severe storms.

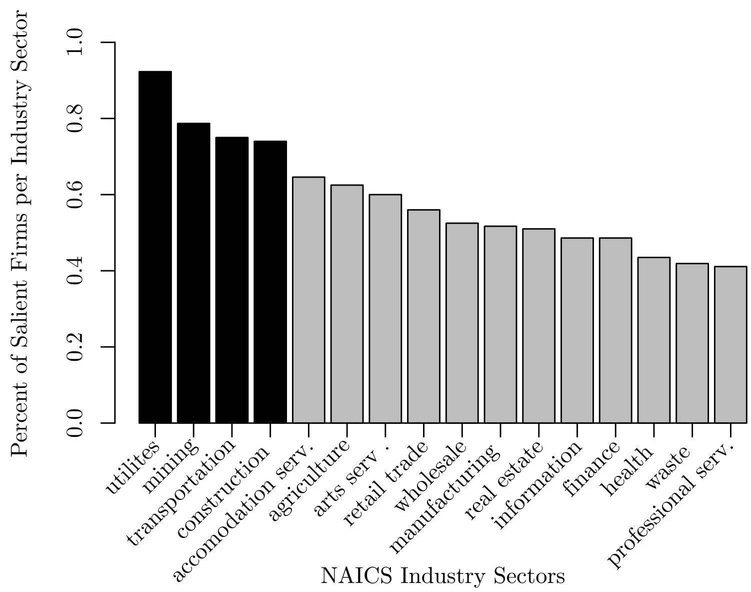


Figure 5: The Percent of Salient Firms per Industry Sectors

This figure shows the percentage of salient firms per industry sector in the North American Industry Classification System (NAICS). Industry sectors not shown in the chart do not contain any salient firms. The black bars highlight the industry sectors in which more than 70% of the firms are salient.

7. Summary and Conclusion

In this paper, we theoretically and empirically investigate the impact of extreme weather risk on firms' cost of equity. Building on a consumption-based asset pricing model with heterogeneous agents in the spirit of Constantinides & Duffie (1996), we identify two conditions for a storm risk premium in the cross-section of stock returns. The first condition demands that extreme weather risk is positively correlated with consumption growth or consumption inequality; the second condition requires that a stock's return is negatively related to extreme weather risk.

We examine both conditions empirically for severe thunderstorm losses in the U.S. We find evidence for the first condition in the period from 1995 to 2019, which is characterized by a clear upward trend in temperature anomalies and elevated thunderstorm activity. For the same period, we find that stocks of domestic firms with the most negative thunderstorm risk betas have significantly larger future returns than stocks with the most positive betas. Based on this finding, we create a zero-investment portfolio with a positive average excess return of 6.5% p.a. This storm risk premium is neither explained by traditional asset pricing risk factors nor firm characteristics, such as size, idiosyncratic volatility or coskewness. Moreover, it withstands are variety of robustness tests.

We explore the properties of the storm risk premium by screening NMP for the seasonal pattern of the underlying thunderstorm risk. We also examine the presence versus absence of the risk premium for exposed and unexposed firms. In line with our expectation, we find that the storm premium is large and statistically significant only for the subsample of exposed firms. Finally, we explore the role of salience, using a textual analysis of firm's financial statements. We find that the storm risk premium only exists for firms that mention storm risk related keywords at least once in their financial statements of the past five years, indicating that investors may not demand a compensation for this form of physical climate risk if they are unaware of a firm's vulnerability.

This study uncovers a new economic channel through which atmospheric natural disaster risk feeds into financial markets. We provide strong empirical evidence that firms which are threatened by extreme weather risk exhibit a higher cost of equity than their unexposed peers. Climate change will exacerbate convective storm risk (Diffenbaugh et al., 2013). It can thus be expected that the storm risk premium demanded by investors will persist or even increase. The question how companies should react to this kind of climate risk exposure a is an interesting topic for future research.

References

Acharya, V., Johnson, T., Sundaresan, S., & Tomunen, T. (2023). Is Physical Climate Risk Priced? Evidence from Regional Variation in Exposure to Heat Stress. *Working Paper*, *SSRN Electronic Journal*.

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature Shocks and Establishment Sales. *Review of Financial Studies*, *33*, 1331–1366.

Aladangady, A., Aron-Dine, S., Dunn, W. E., Feiveson, L., Lengermann, P., & Sahm, C. (2017). The Effect of Hurricane Matthew on Consumer Spending. *Working Paper*, *SSRN Electronic Journal*.

Alok, S., Kumar, N., & Wermers, R. R. (2020). Do Fund Managers Misestimate Climatic Disaster Risk? *Review of Financial Studies*, *33*, 1146–1183.

Andersson, M., Bolton, P., & Samama, F. (2016). Hedging Climate Risk. *Financial Analysts Journal*, *72*, 13–32.

Ang, A., & Chen, J. (2006). Downside Risk. *Review of Financial Studies*, *19*, 1191–1239.

Attanasio, O. P., & Pistaferri, L. (2016). Consumption Inequality. *Journal of Economic Perspectives*, *30*, 2–28.

Auffret, P. (2003). High Consumption Volatility: The Impact of Natural Disasters? *Working Paper, World Bank*, *January*.

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *Journal of Finance*, *61*, 1645–1680.

Baker, S. D., Hollifield, B., & Osambela, E. (2022). Asset Prices and Portfolios with Externalities. *Review of Finance*, *26*, 1433–1468.

Bakkensen, L., & Barrage, L. (2021). Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics: Going Under Water? *Working Paper*, *NBER*.

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does Climate Change Affect Real Estate Prices? Only If You Believe in It. *Review of Financial Studies*, *33*, 1256–1295.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns. *Journal of Financial Economics*, *99*, 427–446.

Barro, R. J. (2006). Rare Disasters and Asset Markets in the Twentieth Century. *Quarterly Journal of Economics*, *121*, 823–866.

Bauer, D., Phillips, R., & Zanjani, G. (2013). Financial Pricing of Insurance. In G. Dionne (Ed.), *Handbook of Insurance* chapter 22. (pp. 627–645). New York, NY: Springer New York.

Belasen, A. R., & Polachek, S. W. (2008). How Hurricanes Affect Wages and Employment in Local Labor Markets. *American Economic Review*, *98*, 49–53.

Berkman, H., Jacobsen, B., & Lee, J. B. (2011). Time-Varying Rare Disaster Risk and Stock Returns. *Journal of Financial Economics*, *101*, 313–332.

Bernstein, A., Gustafson, M., & Lewis, R. (2019). Disaster on the Horizon: The Price Effect of Sea Level Rise. *Journal of Financial Economics*, *134*, 253–272.

Bolton, P., & Kacperczyk, M. T. (2021a). Do Investors Care about Carbon Risk? *Journal of Financial Economics*, *142*, 517–549.

Bolton, P., & Kacperczyk, M. T. (2021b). Signaling through Carbon Disclosure. *Working Paper*, *SSRN Electronic Journal*.

Botzen, W. J., Deschenes, O., & Sanders, M. (2019). The Economic Impacts of Natural Disasters: A Review of Models and Empirical Studies. *Review of Environmental Economics and Policy*, *13*, 167–188.

Braun, A. (2016). Pricing in the Primary Market for Cat Bonds: New Empirical Evidence. *Journal of Risk and Insurance*, *83*, 811–847.

Braun, A., Luca, D., & Schmeiser, H. (2019). Consumption-Based Asset Pricing in Insurance Markets: Yet Another Puzzle? *Journal of Risk and Insurance*, *86*, 629–661.

Brooks, H. (2013). Severe Thunderstorms and Climate Change. *Atmospheric Research*, *123*, 129–138. 6th European Conference on Severe Storms 2011. Palma de Mallorca, Spain.

Brown, J. R., Gustafson, M., & Ivanov, I. (2021). Weathering Cash Flow Shocks. *Journal of Finance*, *76*, 1731–1772.

Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2022). Transition Versus Physical Climate Risk Pricing in European Financial Markets: A Text-Based Approach. *Working Paper*, *SSRN Electronic Journal*.

Campbell, J. (2003). Consumption-Based Asset Pricing. In G. Constantinides,

M. Harris, & R. Stulz (Eds.), *Handbook of the Economics of Finance* chapter 13. (pp. 801–885). Elsevier B.V. (Volume 1 ed.).

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, *52*, 57–82.

Cavallo, E. A., Galiani, S., Noy, I., & Pantano, J. (2013). Catastrophic Natural Disasters and Economic Growth. *Review of Economics and Statistics*, *95*, 1549–1561.

Chabi-Yo, F., Ruenzi, S., & Weigert, F. (2018). Crash Sensitivity and the Cross Section of Expected Stock Returns. *Journal of Financial and Quantitative Analysis*, *53*, 1059–1100.

Chen, Z., & Yang, B. (2019). In Search of Preference Shock Risks: Evidence from Longevity Risks and Momentum Profits. *Journal of Financial Economics*, *133*, 225–249.

Cohen, L., Malloy, C., & Nguyen, Q. (2020). Lazy Prices. *Journal of Finance*, *75*, 1371–1415.

Collier, B. L., Haughwout, A. F., Kunreuther, H. C., & Michel-Kerjan, E. O. (2020). Firms' Management of Infrequent Shocks. *Journal of Money, Credit and Banking*, *52*, 1329–1359.

Constantinides, G. M., & Duffie, D. (1996). Asset Pricing with Heterogeneous Consumers. *Journal of Political Economy*, *104*, 219–240.

Cortés, K. R., & Strahan, P. E. (2017). Tracing out Capital Flows: How Financially Integrated Banks Respond to Natural Disasters. *Journal of Financial Economics*, *125*, 182–199.

Cummins, J. D. (2006). Should the Government Provide Insurance for Catastrophes? *Federal Reserve Bank of St. Louis Review*, *88*, 337–379.

Cummins, J. D., & Trainar, P. (2009). Securitization, Insurance, and Reinsurance. *Journal of Risk and Insurance*, *76*, 463–492.

Custodio, C., Ferreira, M. A., Garcia-Appendini, E., & Lam, A. (2021). Economic Costs of Climate Change. *Working Paper*, *SSRN Electronic Journal*.

Denis, D. J., Denis, D. K., & Yost, K. (2002). Global Diversification, Industrial Diversification, and Firm Value. *Journal of Finance*, *57*, 1951–1979.

Dessaint, O., & Matray, A. (2017). Do Managers Overreact to Salient Risks? Evidence from Hurricane Strikes. *Journal of Financial Economics*, *126*, 97–121.

Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). Climate Value at Risk' of Global Financial Assets. *Nature Climate Change*, *6*, 676–679.

Diffenbaugh, N. S., Scherer, M., & Trapp, R. J. (2013). Robust Increases in Severe Thunderstorm Environments in Response to Greenhouse Forcing. *Proceedings of the National Academy of Sciences*, *110*, 16361–16361.

Döhrmann, D., Gürtler, M., & Hibbeln, M. (2017). Insured Loss Inflation: How Natural Catastrophes Affect Reconstruction Costs. *Journal of Risk and Insurance*, *84*, 851–879.

Engle, R. F., Giglio, S., Lee, H., Kelly, B. T., & Stroebel, J. (2020). Hedging Climate Change News. *Review of Financial Studies*, *33*, 1184–1216.

Fama, E. F., & French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, *33*, 3–56.

Fama, E. F., & French, K. R. (2015). A Five-Factor Asset Pricing Model. *Journal of Financial Economics*, *116*, 1–22.

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*, 607–636.

Felbermayr, G., & Gröschl, J. (2014). Naturally Negative: The Growth Effects of Natural Disasters. *Journal of Development Economics*, *111*, 92–106.

Frazzini, A., & Pedersen, L. H. (2014). Betting Against Beta. *Journal of Financial Economics*, *111*, 1–25.

Froot, K. A. (2001). The Market for Catastrophe Risk: A Clinical Examination. *Journal of Financial Economics*, *60*, 271–529.

Gabaix, X. (2012). Variable Rare Disasters: An Exactly Solved Framework for Ten Puzzles in Macro-Finance. *Quarterly Journal of Economics*, *127*, 645–700.

Gomes, F., & Michaelides, A. (2011). Asset Pricing with Limited Risk Sharing and Heterogeneous Agents. *Review of Financial Studies*, *21*, 415–448.

Gostlow, G. (2022). Pricing Physical Climate Risk in the Cross-Section of Returns. *Working Paper*, *SSRN Electronic Journal*.

Gourevitch, J. D., Kousky, C., Liao, Y. P., Nolte, C., Pollack, A. B., Porter, J. R., & Weill, J. A. (2023). Unpriced Climate Risk and the Potential Consequences of Overvaluation in US Housing Markets. *Nature Climate Change*, *13*, 250–257.

Hain, L. I., Kölbel, J. F., & Leippold, M. (2022). Let's get Physical: Comparing Metrics of Physical Climate Risk. *Finance Research Letters*, *46*, 102406.

Hallegatte, S. (2015). The Indirect Cost of Natural Disasters and an Economic Definition of Macroeconomic Resilience. *Working Paper, World Bank*, *July*.

Heaton, J., & Lucas, D. J. (1996). Evaluating the Effects of Incomplete Markets on Risk Sharing and Asset Pricing. *Journal of Political Economy*, *104*, 443–487.

Hoeppe, P. (2016). Trends in Weather Related Disasters – Consequences for Insurers and Society. *Weather and Climate Extremes*, *11*, 70–79.

Holzheu, T., & Turner, G. (2018). The Natural Catastrophe Protection Gap: Measurement, Root Causes and Ways of Addressing Underinsurance for Extreme Events. *Geneva Papers on Risk and Insurance: Issues and Practice*, *43*, 37–71.

Hu, Z. (2022). Social Interactions and Households' Flood Insurance Decisions. *Journal of Financial Economics*, *144*, 414–432.

Ibragimov, R., Jaffee, D., & Walden, J. (2009). Nondiversification Traps in Catastrophe Insurance Markets. *Review of Financial Studies*, *22*, 959–993.

Ilhan, E., Sautner, Z., & Vilkov, G. (2020). Carbon Tail Risk. *Review of Financial Studies*, *34*, 1540–1571.

Jaffee, D. M., & Russell, T. (1997). Catastrophe Insurance, Capital Markets, and Uninsurable Risks. *Journal of Risk and Insurance*, *64*, 205–230.

Jegadeesh, N. (1990). Evidence of Predictable Behavior of Security Returns. *Journal of Finance*, *45*, 881–898.

Jegadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, *48*, 65–91.

Jurek, J. W., & Stafford, E. (2015). The Cost of Capital for Alternative Investments. *Journal of Finance*, *70*, 2185–2226.

Kelly, B., & Jiang, H. (2014). Tail Risk and Asset Prices. *Review of Financial Studies*, *27*, 2841–2871.

Keys, B. J., & Mulder, P. (2020). Neglected No More: Housing Market, Mortgage Lending and Sea Level Rise. *Working Paper*, *NBER*.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *Review of Financial Studies*, *33*, 1067–1111.

Kruttli, M. S., Roth Tran, B., & Watugala, S. W. (2023). Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics. *Working Paper*, *SSRN Electronic Journal*.

Larsen, P. H. (2016). A Method to Estimate the Costs and Benefits of Undergrounding Electricity Transmission and Distribution Lines. *Energy Economics*, *60*, 47–61.

Lontzek, T., Pohl, W., Schmedders, K., Thalhammer, M., & Wilms, O. (2023). Asset Pricing with Disagreement about Climate Risks. *Working Paper*, *SSRN Electronic Journal*.

Mankiw, N. (1986). The Equity Premium and the Concentration of Aggregate Shocks. *Journal of Financial Economics*, *17*, 211–219.

Martin, I. W. R., & Pindyck, R. S. (2015). Averting Catastrophes: The Strange Economics of Scylla and Charybdis. *American Economic Review*, *105*, 2947–2985.

McIntosh, M. F. (2008). Measuring the Labor Market Impacts of Hurricane Katrina Migration: Evidence from Houston, Texas. *American Economic Review*, *98*, 54–57.

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance*, *42*, 483–510.

Michel-Kerjan, E., & Kunreuther, H. (2011). Redesigning Flood Insurance. *Science*, *333*, 408–409.

Miljkovic, T., & Miljkovic, D. (2014). Modeling Impact of Hurricane Damages on Income Distribution in the Coastal U.S. *International Journal of Disaster Risk Science*, *5*, 265–273.

Murfin, J., & Spiegel, M. (2020). Is the Risk of Sea Level Rise Capitalized in Residential Real Estate? *Review of Financial Studies*, *33*, 1217–1255.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*, 703–708.

Odell, K. A., & Weidenmier, M. D. (2004). Real Shock, Monetary Aftershock: The

1906 San Francisco Earthquake and the Panic of 1907. *Journal of Economic History*, *64*, 1002–1027.

Palagi, E., Coronese, M., Lamperti, F., & Roventini, A. (2022). Climate Change and the Nonlinear Impact of Precipitation Anomalies on Income Inequality. *Proceedings of the National Academy of Sciences*, *119*, e2203595119.

Pástor, L., & Stambaugh, R. F. (2003). Liquidity Risk and Expected Stock Returns. *Journal of Political Economy*, *111*, 642–685.

Pindyck, R. S., & Wang, N. (2013). The Economic and Policy Consequences of Catastrophes. *American Economic Journal: Economic Policy*, *5*, 306–339.

Rehse, D., Riordan, R., Rottke, N., & Zietz, J. (2019). The Effects of Uncertainty on Market Liquidity: Evidence from Hurricane Sandy. *Journal of Financial Economics*, *134*, 318–332.

Rietz, T. A. (1988). The Equity Risk Premium: A Solution. *Journal of Monetary Economics*, *22*, 117–131.

Roth Tran, B. (2019). Divest, Disregard, or Double Down? *American Economic Review: Insights*, *1*, 241–256.

Ruenzi, S., Ungeheuer, M., & Weigert, F. (2020). Joint Extreme Events in Equity Returns and Liquidity and Their Cross-sectional Pricing Implications. *Journal of Banking & Finance*, *115*.

Sadka, R. (2006). Momentum and Post-Earnings-Announcement Drift Anomalies: The Role of Liquidity Risk. *Journal of Financial Economics*, *80*, 309–349.

Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2023a). Pricing Climate Change Exposure. *Management Science*, *forthcoming*.

Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023b). Firm-Level Climate Change Exposure. *Journal of Finance*, *78*, 1449–1498.

Sawada, Y., & Shimizutani, S. (2007). Consumption Insurance Against Natural Disasters: Evidence from the Great Hanshin-Awaji (Kobe) Earthquake. *Applied Economics Letters*, *14*, 303–306.

Sawada, Y., & Shimizutani, S. (2008). How Do People Cope with Natural Disasters? Evidence from the Great Hanshin-Awaji (Kobe) Earthquake in 1995. *Journal of Money, Credit and Banking*, *40*, 463–488.

Schubert, V. (2022). Is Flood Risk Priced in Bank Returns? *Working Paper*, *SSRN Electronic Journal*.

Schüwer, U., Lambert, C., & Noth, F. (2019). How do Banks React to Catastrophic Events? Evidence from Hurricane Katrina. *Review of Finance*, *23*, 75–116.

Smiley, K. T., Noy, I., Wehner, M. F., Frame, D., Sampson, C. C., & Wing, O. E. J. (2022). Social Inequalities in Climate Change-Attributed Impacts of Hurricane Harvey. *Nature Communications*, *13*, 3418.

Söderlind, P. (2009). An Extended Stein's Lemma for Asset Pricing. *Applied Economics Letters*, *16*, 1005–1008.

Stern, N. (2008). The Economics of Climate Change. *American Economic Review*, *98*, 1–37.

Strobl, E. (2011). The Economic Growth Impact of Hurricanes: Evidence from U.S. Coastal Counties. *Review of Economics and Statistics*, *93*, 575–589.

Sun, C., Xu, J., & Yihui, Y. (2021). Climate Change Exposure and Stock Return Predictability. *Working Paper*, *SSRN Electronic Journal*.

Swiss Re (2020). Natural Catastrophes in Times of Economic Accumulation and Climate Change. *Industry Report*, *February*.

Swiss Re (2022). Natural Catastrophes and Inflation in 2022: A Perfect Storm. *Industry Report*, *February*.

Swiss Re (2023). Severe Thunderstorms Account for up to 70Insured Natural Catastrophe Losses in First Half of 2023, Swiss Re Institute Estimates. *Press Release*, *August*.

Trapp, R. J., Diffenbaugh, N. S., Brooks, H. E., Baldwin, M. E., Robinson, E. D., & Pal, J. S. (2007). Changes in Severe Thunderstorm Environment Frequency During the 21st Century Caused by Anthropogenically Enhanced Global Radiative Forcing. *Proceedings of the National Academy of Sciences*, *104*, 19719–19723.

Tubaldi, R. (2021). Mutual Funds' Fire Sales and the Real Economy: Evidence from Hurricanes. *Working Paper*, *SSRN Electronic Journal*.

del Valle, A., de Janvry, A., & Sadoulet, E. (2020). Rules for Recovery: Impact of Indexed Disaster Funds on Shock Coping in Mexico. *American Economic Journal: Applied Economics*, *12*, 164–195.

Vilier, J., Kok, M., & Nicolai, R. P. (2014). Assessment of the Losses Due to Business Interruption Caused by Large-Scale Floods. In *Safety, Reliability and Risk Analysis: Beyond the Horizon - Proceedings of the European Safety and Reliability Conference, ESREL 2013* (pp. 2415–2423).

Wachter, J. A. (2013). Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility? *Journal of Finance*, *68*, 987–1035.

Weil, P. (1992). Equilibrium Asset Prices with Undiversifiable Labor Income Risk. *Journal of Economic Dynamics and Control*, *16*, 769–790.

Wing, O., Pinter, N., Bates, P., & Kousky, C. (2020). New Insights into US Flood Vulnerability Revealed from Flood Insurance Big Data. *Nature Communications*, *11*.

Zanjani, G. (2002). Pricing and Capital Allocation in Catastrophe Insurance. *Journal of Financial Economics*, *65*, 283–305.

Zanocco, C., Flora, J., & Boudet, H. (2022). Disparities in Self-Reported Extreme Weather Impacts by Race, Ethnicity, and Income in the United States. *PLOS Climate*, *1*, 1–20.

8. Appendix

8.1. Decomposing Correlations

Consider three random variables X, Y and Z. If X is correlated with Y and Y is correlated with Z, then X must also be correlated with Z. To see this, assume that all three random variables have a zero mean ($\mathbb{E}[X] = \mathbb{E}[Y] = \mathbb{E}[Z] = 0$) and unit variance ($\mathbb{E}[X^2] - \mathbb{E}[X]^2 = \mathbb{E}[Y^2] - \mathbb{E}[Y]^2 = \mathbb{E}[Z^2] - \mathbb{E}[Z]^2 = 1$). This can always be achieved by demeaning and standardizing the variables. Now, express X and Z as linear combinations of Y and a second component denoted X^* and Z^*, respectively, which is independent of Y:

$$X = aY + X^*, \tag{9}$$

$$Z = bY + Z^*. \tag{10}$$

The expectation of X times Y is

$$\begin{aligned} \mathbb{E}[XY] &= \mathbb{E}[(aY + X^*)\, Y] \\ &= a\mathbb{E}[Y^2] + \mathbb{E}[YX^*], \end{aligned} \tag{11}$$

and the expectation of Z times Y equals

$$\begin{aligned} \mathbb{E}[ZY] &= \mathbb{E}[(bY + Z^*)\, Y] \\ &= b\mathbb{E}[Y^2] + \mathbb{E}[YZ^*]. \end{aligned} \tag{12}$$

$\mathbb{E}[YX^*]$ and $\mathbb{E}[YZ^*]$ are zero by design. Recall that X and Y have zero means and unit variances, implying that their standard deviations are $\sqrt{\mathbb{E}[X^2]} = 1$ and

$\sqrt{\mathbb{E}[Y^2]} = 1$. Consequently, a and b represent the correlations between X and Y ($\rho[X,Y]$) as well as Z and Y ($\rho[Z,Y]$):

$$
\begin{aligned}
a &= \mathbb{E}[XY] = \frac{\mathbb{E}[XY]}{\sqrt{\mathbb{E}[X^2] \cdot \mathbb{E}[Y^2]}} = \rho[X,Y], && (13) \\
b &= \mathbb{E}[ZY] = \frac{\mathbb{E}[ZY]}{\sqrt{\mathbb{E}[Z^2] \cdot \mathbb{E}[Y^2]}} = \rho[Z,Y]. && (14)
\end{aligned}
$$

Next, we derive the variances of X^* and Z^*. To this end, first rewrite the variances of X and Z, using (9) and (10):

$$
\begin{aligned}
\mathbb{E}[X^2] &= a^2\mathbb{E}[Y^2] + 2a\mathbb{E}[YX^*] + \mathbb{E}[X^{*2}] && (15) \\
&= a^2 + \mathbb{E}[X^{*2}] = 1,
\end{aligned}
$$

$$
\begin{aligned}
\mathbb{E}[Z^2] &= b^2\mathbb{E}[Y^2] + 2b\mathbb{E}[YZ^*] + \mathbb{E}[Z^{*2}] && (16) \\
&= b^2 + \mathbb{E}[Z^{*2}] = 1.
\end{aligned}
$$

Insert $a = \rho[X,Y]$ and $b = \rho[Z,Y]$ to obtain the following expressions for the variances of X^* ($\mathbb{E}[X^{*2}]$) and Z^* ($\mathbb{E}[Z^{*2}]$):

$$
\begin{aligned}
\mathbb{E}[X^{*2}] &= 1 - \rho[X,Y]^2, && (17) \\
\mathbb{E}[Z^{*2}] &= 1 - \rho[Z,Y]^2. && (18)
\end{aligned}
$$

Finally, inserting $a = \rho[X, Y]$ and $b = \rho[Z, Y]$ in (9) and (10) and taking the expectation of X times Z, delivers the correlation of X and Z ($\rho[X, Z]$) as a function of $\rho[X, Y]$ and $\rho[Z, Y]$:

$$\begin{aligned}
\rho[X, Z] &= (\mathbb{E}[XZ] - \underbrace{\mathbb{E}[X] \cdot \mathbb{E}[Z]}_{=0}) / \underbrace{\sqrt{(\mathbb{E}[X^2] - \mathbb{E}[X]^2) \cdot (\mathbb{E}[Z^2] - \mathbb{E}[Z]^2)}}_{=1} \qquad (19) \\
&= \rho[X, Y] \cdot \rho_t[Z, Y] \cdot \mathbb{E}[Y^2] + \rho[X, Y] \cdot \underbrace{\mathbb{E}[YZ^*]}_{=0} \\
&+ \rho[Z, Y] \cdot \underbrace{\mathbb{E}[YX^*]}_{=0} + \mathbb{E}[X^* Z^*] \\
&= \rho[X, Y] \cdot \rho[Z, Y] + \mathbb{E}[X^* Z^*].
\end{aligned}$$

Hence, the sign of $\rho[X, Z]$ depends on the product of $\rho[X, Y]$ and $\rho[Z, Y]$. More specifically, $\rho[X, Z]$ will be positive, if both $\rho[X, Y]$ and $\rho[Z, Y]$ are positive or negative. On the other hand, $\rho[X, Z]$ will be negative, if $\rho[X, Y]$ is negative and $\rho[Z, Y]$ is positive, or vice versa. Apart from the correlations $\rho[X, Y]$ and $\rho[Z, Y]$, the strength of $\rho[X, Z]$ additionally depends on the expectation $\mathbb{E}[X^* Z^*]$. Dissecting the latter by means of $cov\,[X^*, Z^*] = \mathbb{E}\,[X^* Z^*] - \mathbb{E}\,[X^*] \cdot \mathbb{E}\,[Z^*]$ yields:

$$\mathbb{E}[X^* Z^*] = \rho[X^*, Z^*] \sqrt{\mathbb{E}[X^{*2}] \cdot \mathbb{E}[Z^{*2}]} + \mathbb{E}[X^*] \cdot \mathbb{E}[Z^*]. \qquad (20)$$

For given means and standard deviations of X^* and Z^*, $\mathbb{E}[X^* Z^*]$ will take on the largest possible value for $(\rho[X^*, Z^*]) = 1$ and the smallest possible value for $(\rho[X^*, Z^*]) = -1$.

8.2. Anecdotal Evidence From Annual 10-K Reports

Industry	Company Name	Extract of Annual Reports (10-K)
Utility	Oklahoma Gas and Electric Company (10-K filed on March 28, 2002)	"The Company has added new generation capacity to meet growing customer demand and has about, in no small part...in no small part, by a series of record-breaking storms, including a 1995 windstorm in the Oklahoma City area affecting 175,000 customers, 1999 tornadoes affecting about 150,000 customers and knocking out a power plant, July 2000 thunderstorms affecting 110,000 customers, a Christmas 2000 ice storm affecting 140,000 customers, Memorial Day 2001 storms leaving 143,000 customers without power and at least two other storms affecting at least 100,000 customers each."
Mining	Gold Resource Corporation (10-K filed on February 29, 2012)	"For approximately six weeks during the cleanup phase following the storm, we were unable to remove ore from the underground mine and supplemented approximately 20% of the mill throughput with stockpiled open pit ore."
Transportation	Spirit Airlines, Inc. (10-K filed on February 2, 2016)	"For example, during the second quarter of 2015, we experienced consecutive storm systems in Dallas, Chicago, New York and Detroit followed by Tropical Storm Bill that sat over Houston before moving north to Dallas. The timing and location of these storm systems produced a domino effect on our operations resulting in over 500 flight cancellations and numerous flight delays, which resulted in an adverse effect on our results of operations."
Construction	Dycom Industries Incorporation (10-K filed on March 4, 2019)	"Additionally, we earned $42.9 million and $35.1 million of contract revenues from storm restoration services during fiscal 2019 and the twelve months ended January 27, 2018, respectively, excluding amounts from acquired businesses."

Table 12: Anecdotal Evidence for the Impact of Severe Convective Storm Risk on Firms

cfr working paper series

centre for financial research cologne

cfr working papers are available for download from www.cfr-cologne.de.

2023

No.	Author(s)	Title
23-08	A. Braun, J. Braun, F. Weigert	Extreme Weather Risk and the Cost of Equity
23-07	A. G. Huang, R. Wermers, J. Xue	“Buy the Rumor, Sell the News”: Liquidity Provision by Bond Funds Following Corporate News Events
23-06	J. Dörries, O. Korn, G. J. Power	How Should the Long-term Investor Harvest Variance Risk Premiums?
23-05	V. Agarwal, W. Jiang, Y. Luo, H. Zou	The Real Effect of Sociopolitical Racial Animus: Mutual Fund Manager Performance During the AAPI Hate
23-04	V. Agarwal, B. Barber, S. Cheng, A. Hameed, H. Shanker, A. Yasuda	Do Investors Overvalue Startups? Evidence from the Junior Stakes of Mutual Funds
23-03	A. Höck, T. Bauckloh, M. Dumrose, C. Klein	ESG Criteria and the Credit Risk of Corporate Bond Portfolios
23-02	T. Bauckloh, J. Dobrick, A. Höck, S. Utz, M. Wagner	“In partnership for the goals”? The (dis)agreement of SDG ratings
23-01	F. Simon, S. Weibels, T. Zimmermann	Deep Parametric Portfolio Policies

2022

No.	Author(s)	Title
22-12	V. Agarwal, A. Cochardt, V. Orlov	Birth Order and Fund Manager’s Trading Behavior: Role of Sibling Rivalry
22-11	G. Cici, S. Gibson, N. Qin, A. Zhang	The Performance of Corporate Bond Mutual Funds and the Allocation of Underpriced New Issues
22-10	E. Theissen, C. Westheide	One for the Money, Two for the Show? The Number of Designated Market Makers and Liquidity
22-09	R. Campbell, P. Limbach, J. Reusche	Once Bitten, Twice Shy: Failed Deals and Subsequent M&A Cautiousness
22-08	M. Gehde-Trapp, L. Klingler	The Effect of Sentiment on Institutional Investors: A Gender Analysis
22-07	T. Bauckloh, V. Beyer, C. Klein	Does it Pay to Invest in Dirty Industries? – New Insights on the Shunned-Stock Hypothesis

22-06	J. Balthrop and G. Cici	Conflicting Incentives in the Management of 529 Plans
22-05	I. T. Ivanov, T. Zimmermann, N. W. Heinrich	Limits of Disclosure Regulation in the Municipal Bond Market
22-04	M. Ammann, A. Cochardt, S. Straumann, F. Weigert	Back to the Roots: Ancestral Origin and Mutual Fund Manager Portfolio Choice
22-03	A. Betzer, J. Gider, P. Limbach	Do Financial Advisors Matter for M&A Pre-Announcement Returns?
22-02	S. Lesmeister, P. Limbach, P.R. Rau, F. Sonnenburg	Indexing and the Performance-Flow Relation of Actively Managed Mutual Funds
22-01	T. Bauckloh, C. Klein, T. Pioch, F. Schiemann	Under Pressure: The Link between Mandatory Climate Reporting and Firms' Carbon Performance

2021

No.	Author(s)	Title
21-11	V. Agarwal, H. Ren, K. Shen, H. Zhao	Redemption in Kind and Mutual Fund Liquidity Management
21-10	N.C. Brown, W. B. Elliott, R. Wermers, R. M. White	News or noise: Mobile internet technology and stock market activity
21-09	V. Agarwal, B. Barber, S. Cheng, A. Hameed, A. Yasuda	Private Company Valuations by Mutual Funds
21-08	T.G. Bali, H. Beckmeyer, M. Moerke, F. Weigert	Option Return Predictability with Machine Learning and Big Data
21-07	F. Chabi-Yo, M. Huggenberger, F. Weigert	Multivariate Crash Risk
21-06	V. Agarwal, H. Aslan, L. Huang, H. Ren	Political Uncertainty and Household Stock Market Participation
21-05	G. Cici, P. Zhang	On the Valuation Skills of Corporate Bond Mutual Funds
21-04	V. Agarwal, P. Hanouna, R. Moussawi, C.W. Stahel	Do ETFs Increase the Commonality in Liquidity of Underlying Stocks?
21-03	M. Saglam, T. Tuzun, R. Wermers	Do ETFs Increase Liquidity?
21-02	C. Andres, D. Bazhutov, D. Cumming, P. Limbach	Does Speculative News Hurt Productivity? Evidence from Takeover Rumors
21-01	T.G. Bali, F. Weigert	Hedge Funds and the Positive Idiosyncratic Volatility Effect

This document only covers the most recent CFR working papers. A full list can be found at www.cfr-cologne.de.

centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de