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# Extreme Weather Risk and the Cross-Section of Stock Returns

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# Extreme Weather Risk and the Cross-Section of Stock Returns

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## Abstract

We provide evidence for 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 economy-wide storm losses earned excess returns of 6.5% p.a. over stocks with the most positive sensitivity. This premium can neither be explained by asset pricing risk factors nor by firm characteristics. It prevails for geographically exposed as well as historically affected firms from a broad range of industries. Our results reveal a novel link between climate risk and firm value.

*Keywords:* Extreme Weather Risk, Empirical Asset Pricing, Cross-Section of Stock Returns, Climate Risk

*JEL:* C12, G01, G11, G12, G17

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## 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: Between 2012 and 2022, natural catastrophes caused global economic damages of about $220 billion per year (Swiss Re, 2023a). 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, 2023a). This trend reached a new peak in the first half of 2023, in which the total losses from severe convective storms in the U.S. exceeded $35 billion (Swiss Re, 2023b).

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. We study whether extreme weather risk is priced in the cross-section of stock returns. To adequately proxy for extreme weather, 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 by corporations.

We discuss four theoretical explanations that motivate the existence of a risk premium for a stock's extreme weather exposure. First, investors are known to shun stocks with salient downsides (here: salient weather events) which depresses prices and lets these stocks earn high returns in the future (Cosemans & Frehen, 2021). Second, weather disasters can cause loss cascades in production networks,



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turning idiosyncratic shocks into systematic shocks (Barrot & Sauvagnat, 2016; Buraschi & Tebaldi, 2023). Third, market segmentation may prevent full diversification of investors and gives rise to idiosyncratic risk premia for weather events (Merton, 1987; Kruttli et al., 2023). Fourth, there is limited risk-sharing for weather catastrophes in the economy and their occurrence increases consumer heterogeneity. In the Appendix, we formally derive a risk premium for such uninsurable idiosyncratic shocks by extending the consumption-based asset pricing model of Constantinides & Duffie (1996) with an extreme weather factor.

To empirically investigate whether extreme weather is a priced factor in the cross-section of equity returns, we draw on market and accounting data for U.S. domestic common stocks within the intersection of CSRP and Compustat. We focus on domestic firms because they cannot properly diversify physical and supply chain risks from extreme weather disasters. We proxy aggregate extreme weather risk by log storm loss growth per capita ($LSLG$), which we compute from a long-term data set of U.S. storm losses provided by the Spatial Hazard Events and Losses Database (SHELDUS). Our sample period for the empirical analysis ranges from 01/1995 to 12/2019. We discard observations before 1995 as SHELDUS loss data is known to have significantly improved thereafter (Gall et al., 2009).

We measure monthly risk sensitivities of firms through $LSLG$ betas based on five-year rolling regressions of the stock's excess returns on the Fama & French (1993) and Carhart (1997) factors plus $LSLG$. Firms that suffer in the wake of severe thunderstorms exhibit a negative $LSLG$ beta, whereas firms that benefit



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show a positive *LSLG* beta.[1] Our objective is to relate firms' *LSLG* betas to future excess returns (returns minus the risk-free rate), with the hypothesis in mind that stocks with a negative *LSLG* beta should bear a premium compared to positive *LSLG* beta stocks as the former hedges against extreme weather risk.

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 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 document that the premium is only slightly reduced to 0.526% per month (again, statistically significant at the 5% level). Annualized, this reflects an extreme weather risk premium for the cross-section of domestic stock returns of more than 6%.

We continue to investigate whether the extreme weather risk premium can be explained by other asset pricing risk factors studied in the literature. To this end, we regress the long-short investment portfolio consisting of the highest, positive *LSLG* beta stocks minus the lowest, negative *LSLG* beta stocks on extensions of the Fama & French (1993) and Carhart (1997) models. We refer to this self-financing portfolio as the NMP (negative-minus-positive *LSLG* beta stock) portfolio. As additional factors we utilize the Chabi-Yo et al. (2018) crash risk factor, the Pástor & Stambaugh (2003) liquidity factor, the Sadka (2006) liquidity

[1]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).



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factor, the Baker & Wurgler (2006) sentiment index, the Jurek & Stafford (2015) downside market risk factor, the WTI oil index, the Frazzini & Pedersen (2014) betting-against-beta factor, the Fama and French short- and long-term reversal factors, as well as the Fama & French (2015) operating profitability and investment factors. None of these previously established factors accounts for the spread in mean excess returns earned by the NMP portfolio. Instead, the alpha in all time-series regressions is statistically significant throughout and varies between 0.454% and 0.779% per month.

We also evaluate whether stocks' exposure to extreme weather risk is associated to future returns in value-weighted Fama & MacBeth (1973) regressions. The effect of the $LSLG$ beta on the one-month ahead future excess return is statistically significant and economically strong when we control for a firm's size, market beta, idiosyncratic volatility, coskewness, book-to-market ratio, as well as the past annual and monthly return. Controlling for the full set of these controls, our results reveal that each additional unit in negative $LSLG$ beta, on average, increases the next-month excess return of a stock by 0.152 percentage points (i.e., an annual increase of 1.8%).

Finally, we aim to rationalize the emergence and magnitude of the extreme weather risk premium with additional empirical tests. First, we investigate the relation between extreme weather risk 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. Second, we examine the role of salient historical events in the compensation of extreme weather risk. For this purpose, we download all companies' 10-K,



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10-K405 and 10-KSB filings from the EDGAR website of the U.S. Securities and Exchange Commission (SEC). We define historically affected 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 split the sample into affected as well as unaffected firms and sort on $LSLG$ betas in each of the two subsamples. The NMP premium is emergent only for affected firms. When we break down the subsample of affected firms across industry sectors, we find the highest percentages in utilities, mining, transportation and construction, which exhibit obvious weather risk vulnerabilities. Third, our results reveal that the NMP premium is statistically significant for stocks that are held pre-dominantly by institutions (but not for stocks that are held pre-dominantly by retail investors). We interpret this finding as a confirmation of Ilhan et al. (2020) who observe that particularly institutional investors value climate risk disclosure and are potentially aware of a premium for extreme weather risk.

Our results have several important implications. Foremost, we show that firms which are threatened by extreme weather 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. On top of that, in the face of increasing climate change, the impact of extreme weather risk is expected to accelerate in the future, making it probable that the premium will persist and amplify in the long run.[2] In addition, while insurance coverage

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



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could take pressure off the cost of equity, the price of natural catastrophe insurance is already high and can be expected to grow 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),[3] protection gaps are therefore likely to become wider instead of narrower. Ultimately, 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 contains the theoretical considerations for the extreme weather risk premium. Section 4 introduces the data. Section 5 contains our main empirical analyses, including asset pricing tests and robustness checks. In Section 6, we provide additional tests to rationalize the emergence and magnitude of the extreme weather risk premium. Section 7 concludes.

## 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).[4] The manuscript 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

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

[4]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).



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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, 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 frequent. 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. This allows us to estimate storm risk betas and their asset pricing implications. Third, we offer additional theoretical explanations for the pricing of local extreme weather events that affect subsets of households and firms in the economy.

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 investors (see Roth Tran, 2019; Krueger et al., 2020; Pankratz et al., 2023), 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.

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



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(see Dessaint & Matray, 2017), cash flow shocks (see Brown et al., 2021), reallocation of capital (see Cortés & Strahan, 2017), and credit constraints (see **?**). 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 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 magnifies 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 Motivation

We offer four potential theoretical explanations for an extreme weather risk premium to arise. First, differences in expected returns for extreme weather-risky and non-risky securities can arise due to salience theory. Cosemans & Frehen (2021)



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show that investors overweight salient past events when forming expectations about future returns of an asset. Natural disasters, such as convective storms, are prime examples of salient events which make investors shun weather-risky stocks and, thus, depress their current prices (see also, Tubaldi, 2021; Alok et al., 2020; Huynh & Xia, 2023). As a consequence, stocks with high extreme weather risk offer high returns in the future.

The second explanation is based on contagion in network economies that feeds into asset prices. Firm-level idiosyncratic shocks from natural disasters have been shown to effectively spread through supply-chain networks, inflicting severe losses on both upstream and downstream firms (Barrot & Sauvagnat, 2016; Carvalho et al., 2020; Pankratz & Schiller, 2024). Buraschi & Tebaldi (2023) develop an intertemporal asset pricing framework in the context of an economy in which firms are closely intertwined through supply chains. They show that idiosyncratic shocks may trigger loss cascades in production networks and thus give rise to a risk premium that cannot be explained by traditional factors.

Another case, in which idiosyncratic shocks can be priced has been highlighted by Kruttli et al. (2023), who modify the model of Merton (1987). In the latter, market segmentation precludes proper diversification of investors such that shocks which would be idiosyncratic under the standard capital asset pricing model can affect expected returns.[5]

Finally, the consumption-based asset pricing literature has postulated that idiosyncratic consumption shocks should be priced if they are uninsurable and increase consumer heterogeneity in the economy (see, e.g., Constantinides & Duffie,

[5]Attempts to test this theory in the stock market have delivered mixed results (Fu, 2009; Ang et al., 2006).



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1996, Gomes & Michaelides, 2011). Natural disasters are a typical illustration 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. This theoretical approach is particularly compelling as there is robust 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 Palagi et al., 2022; Zanocco et al., 2022; Smiley et al., 2022).

In the Appendix (Section 7), we therefore extend the consumption-based framework with heterogeneous agents of Constantinides & Duffie (1996) to derive two conditions under which idiosyncratic weather shocks may produce a risk premium. The first one is a significant correlation between macroeconomic fundamentals (log consumption growth or consumption inequality) and $LSLG$. Initial empirical evidence for this condition to be fulfilled is provided in Section 7 (see Table A1). The second one is a negative correlation of a stock's excess return with $LSLG$. In the next section, we introduce the $LSLG$ beta as a measure for a stock's sensitivity to extreme weather losses, based on which we test this condition.[6]

[6]Just as households, businesses are known to be underinsured against storm losses, too (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). We do thus not expect $LSLG$ betas to be notably impacted by insurance as a mitigating factor.



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## 4. Data and Sample Selection

### *4.1. Thunderstorm Losses and Sample Period*

We compute log storm loss growth per capita ($LSLG$) for the United States based on inflation-adjusted (2009 U.S. dollars) thunderstorm loss data (per capita) from the Spatial Hazard Events and Losses Database (SHELDUS)[7]. SHELDUS captures data of a large range of perils like thunderstorms, hurricanes, floods, and wildfires with accompanying 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). The time-series does not show particular time trends (see Appendix, Figure 5) and is confirmed to be stationary by a Dickey-Fuller test.

Our main empirical analysis will focus on the period from 1995 to 2019. We do not utilize data before 1994 as the quality of loss data from SHELDUS is known to be inferior than afterwards.[8] To provide the reader a feeling for the importance of extreme weather events (and corresponding losses) in this time period, Figure 1 plots the yearly number of severe thunderstorms in the U.S. in combination with global temperature anomalies in the same time period. Both variables have been increasing since the 1980s. We run a Chow test to identify a structural break in the time-series of the number of thunderstorms which is confirmed to lie in the year 1995 (F-statistic: 8.7639, p-value: 0.0005). The average number of yearly

[7]We plot the time series of LSLG in the appendix.

[8]As put by the SHELDUS FAQ: "Starting in 1995, NCDC's Storm Data began reporting exact dollar figures and the spatial resolution increased as well. Thus, loss information starting in 1995/96 is spatially and monetarily more accurate than during years prior."



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disaster events jumped from 4402 for the period from 1960 to 1994 to 6642 between 1995 and 2019. This difference in means between the two periods is statistically significant (t-statistic: −5.5318, p-value: 0.0000). Based on these preliminary findings, we are confident that the sample period from 1995 to 2019 is adequate to investigate the existence of a weather risk premium for the cross-section of stock returns in the U.S.[9]

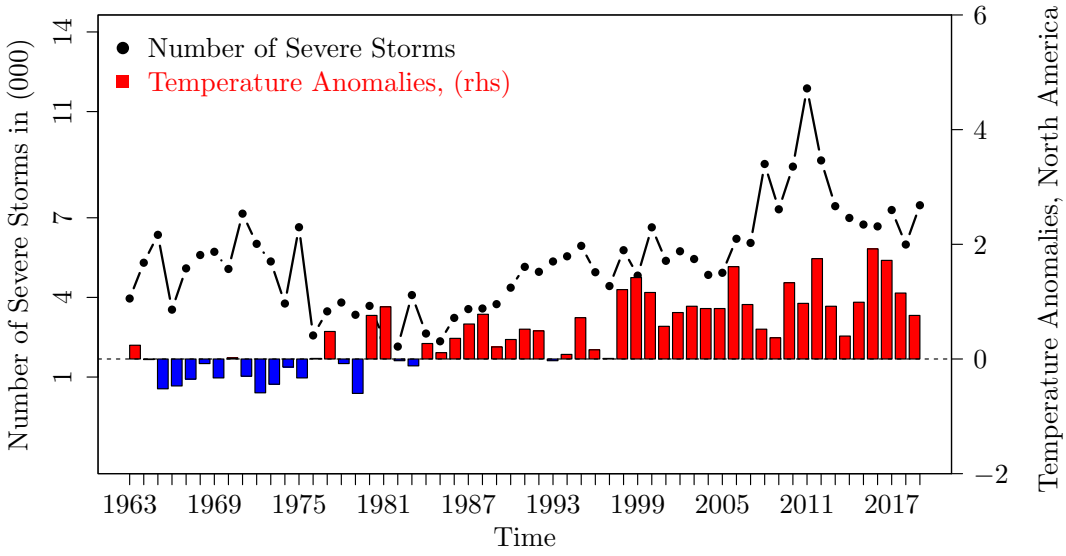



Figure 1: Temperature Anomalies and Number of Severe Thunderstorms

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.

[9]We provide additional evidence for the selection of the sample period in Section 7 of the Appendix. As noted in Section 3, the existence of an extreme weather risk premium in the consumption-based framework is either due to a significant correlation between consumption growth as well as *LSLG* or consumption inequality as well as *LSLG*. We verify that a significant correlation between consumption inequality and *LSLG* is met within the period from 1995 and 2019.



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*4.2. Stock Market and Accounting Data*

In addition to the thunderstorm loss data, we obtain monthly returns, headquarter location, CIK numbers, and relevant firm characteristics of all common stocks traded on the NYSE, AMEX, and NASDAQ from January 1995 to December 2019. These 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.[10] We consider firms to be domestic if they report at least 90% of sales within U.S. borders. Our focus will be on domestic firms since international diversification of sales and assets is a highly plausible remedy against losses from domestic extreme weather events. Our final sample comprises 3'626 domestic firms and 288'577 firm-month return observations.

Table 1 contains summary statistics of relevant firm characteristics. As we will discuss in Section 5.1, *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*. Size is the natural logarithm of a firm's monthly market capitalization. Book-to-market ratios are computed as in 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.[11] Market beta is estimated by means of a 60-month rolling CAPM-regression on the CRSP value-weighted excess market return. Following Ruenzi et al. (2020), we

[10]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.

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



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use standard deviations of the residuals of these regressions as a measure of idiosyncratic volatility. The computation of coskewenss follows Harvey & Siddique (2000) based on a rolling estimation window of 60 months. 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). Finally, following Heston & Sadka (2008), we add lags of 12, 24, and 36 months to account for the seasonality in the cross-section of stock returns.

| **Sample: US Domestic Firms (N = 3'626)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **01/1995–12/2019** | mean | s.d. | skew | kurt | 25% quantile | 50% quantile | 75% quantile |
| $\beta^{\text{LSLG}}$ | 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 last three columns show the 25%-quantile, 50%-quantile (median), and 75%-quantile of each variable. $\beta^{\text{LSLG}}$ (*LSLG* beta) is 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*. Size is the natural logarithm of a firm's market capitalization. Book-to-market (Btm) ratios are computed in line with Fama & French (1993). Market beta (Mkt beta) is estimated by a 60-month rolling CAPM-regression on the CRSP value-weighted excess market return. Idiosyncratic volatility (Id vola) is the standard deviation of the residuals of this market model. Coskewness (Coskew) of the excess returns with the market factor is also estimated based on a 60-month rolling window. We account for short-term reversal (Reversal, in %), 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, in %) (Jegadeesh, 1990; Jegadeesh & Titman, 1993, respectively).



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We complement the descriptive statistics in Table 1 with correlations between the firm characteristics, shown in Table 2. Our results reveal that the correlations between the variables are modest and range between −0.44 (size and idiosyncratic Volatility) to +0.33 (mkt beta and idiosyncratic Volatility). We will take care about these correlations in our empirical analysis.

| **Sample: US Domestic Firms (N = 3'626)** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **01/1995–12/2019** | $\beta^{LSLG}$ | Size | Btm | Mkt beta | Id vola | Coskew | Reversal | Past ret |
| $\beta^{LSLG}$ | 1 | - | - | - | - | - | - | - |
| Size | −0.04 | 1 | - | - | - | - | - | - |
| Btm | +0.02 | −0.13 | 1 | - | - | - | - | - |
| Mkt beta | +0.03 | +0.07 | +0.00 | 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: Correlation Matrix

This table displays linear correlations between the *LSLG* beta as well as independent variables used in this study (pooled over all stocks and months). $\beta^{LSLG}$ (*LSLG* beta) is 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*. Size is the natural logarithm of a firm's market capitalization. Book-to-market (Btm) ratios are computed in line with Fama & French (1993). Market beta (Mkt beta) is estimated by a 60-month rolling CAPM-regression on the CRSP value-weighted excess market return. Idiosyncratic volatility (Id vola) is the standard deviation of the residuals of this market model. Coskewness (Coskew) of the excess returns with the market factor is also estimated based on a 60-month rolling window. We account for short-term reversal (Reversal, in %), 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, in %) (Jegadeesh, 1990; Jegadeesh & Titman, 1993, respectively).



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## 5. Empirical Analysis

### *5.1. LSLG Betas and Univariate Portfolio Sorts*

We begin our main empirical analysis by converting all returns into excess returns by subtracting the contemporary one-month T-Bill rate. Next, we compute stocks' extreme weather risk sensitivities by means of *LSLG* betas, denoted $\beta_i^{LSLG}$. We estimate firm-specific monthly *LSLG* betas using the following time-series regression over the 60 months prior to the sorting date:

$$R_{i,t}^e = \alpha_i + \beta_i^{MKT} MKT_t + \beta_i^{HML} HML_t + \beta_i^{SMB} SMB_t + \beta_i^{MOM} MOM_t + \beta_i^{LSLG} LSLG_t + \epsilon_{i,t}. \quad (1)$$

where $R_{i,t}^e$, $MKT_t$, $HML_t$, $SMB_t$ and $MOM_t$ are the monthly excess returns on stock $i$ and the market, as well as the Fama & French (1993) and Carhart (1997) factors. Stocks of firms that suffer (benefit) in the wake of severe storm events will exhibit a negative (positive) $\beta_i^{LSLG}$.[12] Based on our theoretical motivation in Section 3, we expect that assets with a negative *LSLG* beta should bear a premium compared to positive *LSLG* beta assets as the latter provide extreme weather risk insurance.

To test for this extreme weather risk premium, we first sort the cross-section of domestic stocks into value-weighted quintile portfolios based on their estimated *LSLG* betas in month $t$.[13] We then evaluate value-weighted raw and risk-adjusted

[12] Concrete examples of firms that are impacted by extreme weather escapades are displayed in Table A2 of the Appendix.

[13] In line with Bali et al. (2016), we exclude stocks with the 0.5% lowest market cap in a given month.



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returns in month $t+1$. Portfolio 1 includes the stocks with the lowest $LSLG$ betas (i.e., the most weather-risky assets), whereas portfolio 5 contains the stocks that hedge against extreme weather losses. The row labeled $1-5$ contains the corresponding zero-investment portfolio that buys stocks in portfolio 1 and shorts stocks in portfolio 5. We will hereafter refer to this self-financing portfolio as the NMP (negative minus positive $LSLG$ beta stock) portfolio.

Table 3 repots the empirical results. Column (1) shows that the dispersion in $LSLG$ betas is indeed wide with a cross-sectional distance from $-0.991$ (portfolio 1) to 1.212 (portfolio 5). Column (2) provides first empirical evidence in line with an extreme weather risk premium: Stocks in the portfolio with the lowest $LSLG$ betas earn future monthly excess returns of 1.007%, whereas stocks in the portfolio with the highest $LSLG$ betas earn 0.468%. Hence, the NMP portfolio earns a return of 0.538% per months which is statistically significant at the 5% level. [14] In columns (3) to (5), we risk-adjust the raw return of the NMP portfolio by the capital asset pricing model (CAPM), the Fama & French (1993) three-factor model and the Carhart (1997) four-factor model. We observe that the risk adjustment does not significantly reduce the statistical and economical size of the premium. Annualized, our results reveal an extreme weather risk premium for the cross-section of domestic stock returns of more than 6%.[15]

[14] $t$-statistics are computed using Newey & West (1987) standard errors with four lags.

[15] 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.



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| Sample: US Domestic Firms (N = 3'626) | | | | | |
|---|---|---|---|---|---|
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| 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 3: Univariate Portfolio Sorts

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 period from January 1995 to December 2019. All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5% lowest market capitalization 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.



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*5.2. Time-Series Regressions*

We continue by regressing the time-series return of the NMP portfolio 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 4. Each model in columns (1) to (8) 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 factor (BAB). Furthermore, in models (9) and (10), 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 NMP risk premium of at least 0.454% per month (5.4% p.a.).



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**Sample: US Domestic Firms (01/1995−12/2019)**

| **NMP** | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| MKT | −0.079 | −0.062 | −0.056 | −0.082 | −0.036 | −0.065 | −0.079 | −0.092 | −0.159* | −0.06 |
| SMB | −0.199 | −0.279 | −0.186 | −0.265** | −0.268** | −0.300 | −0.198 | −0.208 | −0.178 | −0.048 |
| HML | 0.222** | 0.185** | 0.263** | 0.246** | 0.230** | 0.209** | 0.263** | 0.303** | 0.189 | 0.044 |
| MOM | 0.173*** | 0.180*** | 0.179*** | 0.185*** | 0.189*** | 0.186*** | 0.173*** | 0.191** | | |
| LTD | | −0.051 | | | | | | | | |
| PS | | | −0.13 | | | | | | | |
| SAD | | | | −2.813 | | | | | | |
| SENT | | | | | 0.231 | | | | | |
| JS | | | | | | 1.579 | | | | |
| WTI | | | | | | | −0.503 | | | |
| BAB | | | | | | | | −0.074 | | |
| REVS | | | | | | | | | 0.044 | |
| REVL | | | | | | | | | −0.009 | |
| RMW | | | | | | | | | | 0.400*** |
| 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 4: Time Series Regressions of NMP on Additional Asset Pricing Factors

This table shows the results for time-series regressions of NMP (value-weighted) on asset pricing factors. To save space, Model (1) contains the market factor (MKT), 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. The sample period is January 1995 to December 2019. t-statistics are based on Newey & West (1987) standard errors with 4 monthly lags. $^{***}$, $^{**}$ and $^{*}$ indicate significance at the one, five, and ten % levels. We report the t-statistics for the abnormal returns (alphas), but not for the regression coefficients.



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*5.3. Fama & MacBeth (1973) Regressions*

Next, we provide multivariate evidence for the existence of an extreme weather risk premium in the form of value-weighted Fama & MacBeth (1973) regressions.[16] Specifically, for each month $t+1$ in the time-series, we run a cross-sectional regression of the realized excess returns of all stocks on their $LSLG$ betas and other firm characteristics from Table 1, as measured for the preceding month $t$. In addition to firm characteristics, we control for potential seasonal effects in stock returns by including the returns for months $t-11$, $t-23$ and $t-35$ as predictors for the return in month $t+1$. These are the 12, 24, and 36 month lags.[17]

Table 5 presents the time-series averages of the monthly cross-sectional regression coefficients together with Newey & West (1987) robust standard errors and significance levels. Our results indicate that – independent of the control variables we utilize – the relation between the $LSLG$ beta and future excess returns remain negative and statistically significant (at least at the 10% level). Based on an unconditional volatility of 1.124 over the sample period (see, Table 1), a one standard deviation decrease of the $LSLG$ beta triggers additional future excess returns between 2.05% and 2.55% per annum (dependent on the exact specification). Our results thus support the notion that stocks with negative $LSLG$ betas earn higher future excess returns than those with positive $LSLG$ betas, and that this spread cannot be explained by asset pricing factors nor by firm characteristics.[18]

[16]We thus follow 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.

[17]As an example, we predict the return in April 2019 with the returns in April 2018, April 2017 and April 2016.

[18]Note that in Table 5, the coefficient estimates on book-to-market, past returns, and reversal differ from many existing empirical asset pricing studies. This is due to our specific sample of domestic firms in the period from 1995 to 2019.



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**Sample: US Domestic Firms (01/1995−12/2019)**

| | (1) $return^e_{(t+1)}$ | (2) $return^e_{(t+1)}$ | (3) $return^e_{(t+1)}$ | (4) $return^e_{(t+1)}$ | (5) $return^e_{(t+1)}$ | (6) $return^e_{(t+1)}$ | (7) $return^e_{(t+1)}$ |
|---|---|---|---|---|---|---|---|
| $\beta_i^{LSLG}$ | −0.189** | −0.183** | −0.171* | −0.172* | −0.169* | −0.152* | −0.159** |
| | (−1.923) | (−1.907) | (−1.836) | (−1.842) | (−1.891) | (−1.824) | (−1.925) |
| Size | −0.010 | −0.031 | −0.032 | −0.028 | −0.031 | −0.051 | −0.071 |
| | (−0.206) | (−0.579) | (−0.593) | (−0.529) | (−0.593) | (−1.011) | (−1.389) |
| Mkt beta | −0.003 | 0.078 | 0.009 | −0.043 | −0.039 | −0.081 | −0.092 |
| | (−0.012) | (0.435) | (0.041) | (−0.196) | (−0.166) | (−0.359) | (−0.420) |
| Id vola | | −0.018 | −0.016 | −0.015 | −0.018 | −0.027 | −0.033 |
| | | (−0.866) | (−0.807) | (−0.031) | (−0.839) | (−0.917) | (−1.871) |
| Coskew | | | −0.279 | −0.346 | −0.286 | −0.296 | −0.158 |
| | | | (−1.002) | (−1.286) | (−1.016) | (−1.161) | (−0.648) |
| Btm | | | | −0.099 | −0.081 | −0.093 | −0.098 |
| | | | | (−1.014) | (−0.851) | (−0.987) | (−1.080) |
| Past ret. | | | | | −0.022** | −0.021*** | −0.021*** |
| | | | | | (−3.022) | (−2.915) | (−2.943) |
| Reversal | | | | | | 0.286 | 0.340 |
| | | | | | | (1.004) | (1.272) |
| Lag12 | | | | | | | −0.008 |
| | | | | | | | (−1.337) |
| Lag24 | | | | | | | 0.002 |
| | | | | | | | (0.437) |
| Lag36 | | | | | | | 0.016*** |
| | | | | | | | (2.617) |
| alpha | 0.774 | 1.056** | 1.065** | 1.113** | 1.163*** | 0.901*** | 1.535*** |
| | (1.684) | (2.032) | (2.033) | (2.104) | (2.246) | (2.863) | (3.291) |

This table presents the results of multivariate value-weighted Fama & MacBeth (1973) regressions of excess returns in month $t+1$ on *LSLG* Betas and a set of firm characteristics measured in month $t$. The latter are size (log of market capitalization), market beta (Mkt beta), idiosyncratic return volatility (Id vola), coskewness of the stock's excess returns with the market's excess returns (Coskew), book-to-market ratio (Btm), the return between $t-11$ and $t-1$ (Past return), the return between $t-1$ and $t$ return (Reversal), and the 12, 24 and 36 Lags of the return in t+1. The sample period is January 1995 to December 2019. All t-statistics are based on Newey & West (1987) standard errors with 4 monthly lags. ***, **, and * indicate significance at the one, five, and ten % levels. We report the t-statistics for the abnormal returns (alphas), but not for the regression coefficients.

Table 5: Regressions with *LSLG* Betas and Firm Characteristics



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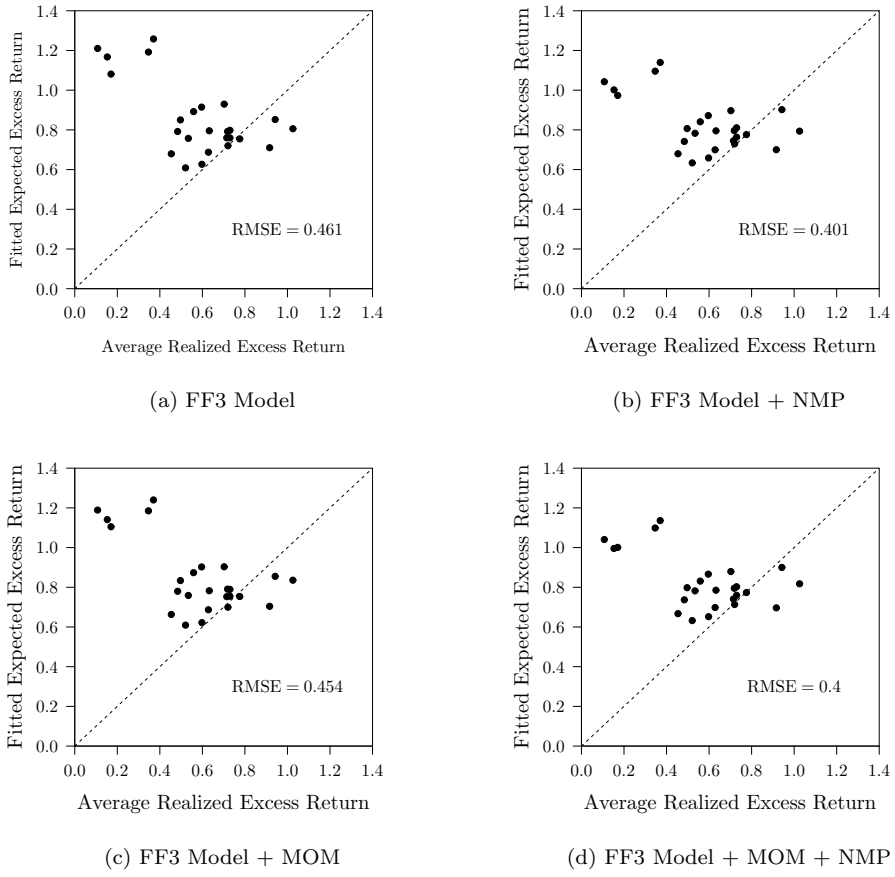
*5.4. Asset Pricing Implications for Test Portfolios and Robustness*

Can the NMP portfolio help to price common test portfolios from the literature more precisely? To answer this question, Figure 2 plots the model-predicted monthly expected excess returns (vertical axis) against the average monthly realized excess returns (horizontal axis) for 25 test portfolios sorted by size and momentum. Test portfolios for which the models' pricing errors are small should closely align along the 45-degree line. Quantitatively, we inspect how the root-mean-square error (RMSE) of the test portfolios to the 45-degree line changes if NMP is added as a pricing variable. Our results reveal that the NMP extension reduces the RMSE from 0.461 to 0.401 for the Fama & French (1993) three-factor model in Panels A and B. It also decreases the RMSE from 0.454 to 0.400 for the Carhart (1997) in Panels C and D. A Diebold-Mariano test confirms that these reductions are statistically significant (p-values: 0.009 and 0.010). Hence, NMP carries pricing information not included in MKT, HML, SMB, and MOM and, consequently, helps to explain the cross-section of expected stock returns.

Finally, Table 6 shows the results of two robustness tests for the existence of an extreme weather premium. In Panel A we find that stocks with low $LSLG$ betas earn higher future risk-adjusted returns than stocks with high $LSLG$ betas when we restrict our sample to the 50% largest domestic stocks. Hence, it is unlikely that illiquidity effects or trading frictions drive our results. Panel B confirms stability of our results when we measure sensitivities with $LSLG$ correlations instead of $LSLG$ betas.



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(a) FF3 Model

(b) FF3 Model + NMP

(c) FF3 Model + MOM

(d) FF3 Model + MOM + NMP

Figure 2: NMP and Test Portfolios

In this figure, the model-predicted expected excess returns (vertical axis) for 25 test portfolios sorted by size and momentum (received from Kenneth French's website) 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, SMB, HML) and the Carhart (1997) four-factor model (MKT, SMB, HML, UMD). Subfigures (b) and (d) show both models extended by NMP. All four subfigures contain the RMSE achieved by the respective models. The sample period is January 1995 to December 2019.



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**Panel A: 50% Largest Domestic Firms**

| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
|---|---|---|---|---|---|
| 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***

| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
|---|---|---|---|---|---|
| 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 6: Robustness Tests: Firm Size and *LSLG* Correlation

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 period from January 1995 to 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. 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.



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## 6. Additional Empirical Tests

In this section, we rationalize the emergence and magnitude of the extreme weather risk premium for the cross-section of stock returns with additional tests.

### *6.1. Geographical Exposure to Extreme Weather Risk*

We begin by splitting our sample of domestic firms based on geographical exposure to historical weather events. To this end, we split the sample in two parts: Firms with headquarters in US states which were historically exposed to significant thunderstorm activity and firms headquartered in states that were not. We decide on this differentiation between states based on data from the National Oceanic and Atmospheric Association (NOAA). A firm is referred to as geographically exposed if the NOAA reports an annual average of at least ten severe weather days in the period from 2003 to 2012.[19] The resulting exposure pattern is shown in Figure 3 and documents a strong geographic East-West split with firms headquartered on the US East Coast being exposed.[20]

To investigate whether the premium for extreme weather exposure is dependent on geographical exposure of firms, we perform univariate portfolio sorts between $LSLG$ betas in month $t$ as well as future excess returns and alphas in month $t+1$ (as in Table 3). Table 7 reports the results. For geographically exposed firms, the NMP portfolio delivers an economically large risk-adjusted return of more than 0.7% per month (i.e., more than 8% per annum) while being statistically significant at the 1% level. To the contrary, portfolio sorts for firms that

[19]Severe weather days are defined as days with at least one tornado, wind, and/or hail report within 25 miles. The data period is determined by the NOAA map.

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



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are not geographically exposed deliver abnormal return spreads close to zero.[21] Hence, geographic exposure of firms' headquarters is a strong determinant for the existence and magnitude of the extreme weather risk premium in the U.S.

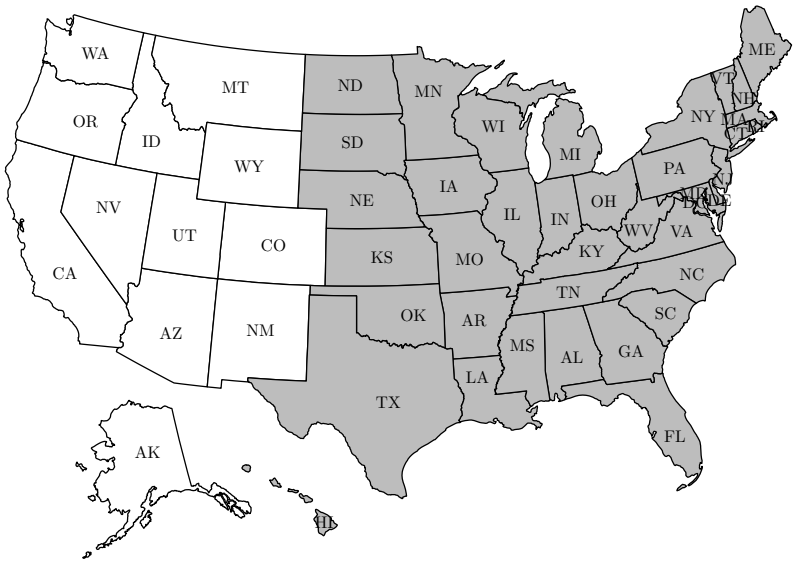



Figure 3: Geographic Thunderstorm Exposure

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

[21]Note that the number of firms in Table 7 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.



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*6.2. Historically Affected vs. Unaffected Firms*

In a second step, we explore the relevance of actual, historical events for the extreme weather 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 CRSP/Compustat data.[22] We then perform a textual analysis on the financial statements, using the keywords "severe storm", "storms", and "thunderstorm" (both lowercase and capitalized). We define historically affected firms as those that mention these keywords at least once in their financial statements of the five years before the respective portfolio sorting date.[23]

We inspect whether the degree of the extreme weather risk premium varies according to whether a firm has been historically affected (i.e., dynamically, over the past five years) by a storm or not. For this purpose, we divide the cross-section of domestic stock returns into historically affected vs. non-affected firms and conduct univariate portfolio sorts for both subsamples. Table 8 reports the results of this analysis. We document a strong extreme weather risk premium for historically affected firms in Panel A. In this subsample, stocks with the lowest $LSLG$ beta earn risk-adjusted returns of more than 0.7% per month (i,e,, more than 8% per annum) than stocks with the highest $LSLG$ beta. In contrast, we do not find a significant extreme weather premium for non-affected firms in Panel B. In summary, investors require a compensation for the extreme weather risk of a stock when they know that it has been affected already in the close past. These

[22]The reports have been accessible since 2000.

[23]The number of stocks shrinks to 3'548 because it was not possible to match the CRSP/Compustat data with EDGAR in all cases.



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| **Panel A: Geographically Exposed Firms ($N$ = 2'693)** | | | | | |
|---|---|---|---|---|---|
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| 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)** | | | | | |
|---|---|---|---|---|---|
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| 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 7: Portfolio Sorts for Geographically Exposed vs. Unexposed 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 period from January 1995 to December 2019. We differentiate between geographically-exposed and unexposed firms. A firm is referred to as geographically exposed if the NOAA reports an annual average of at least ten severe thunderstorms days in the period from 2003 to 2012. All portfolios are formed on a value-weighted basis. We exclude the stocks with the 0.5% lowest market capitalization 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.



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results align nicely with the "salience" motivation provided in Section 3.

We also examine whether the extreme weather risk premium is concentrated in a particular industry sector. To this end, we break down the subsample of affected firms and display the percentage of affected firms among the total firms in NAIC industry sectors in Figure 4. Industry sectors not shown in the bar chart do not contain any affected firms. We derive at least two insights from this analysis.

First, our results for the extreme weather risk premium are not predominantly driven by a single industry sector implying that different types of corporations and business models are exposed to extreme weather risk. Second, four industry sectors particularly stand out, with more than 70% of the respective firms been affected at least once during our sample period: Utilities, mining, transportation, and construction. Notably, the same sectors have been highlighted as being affected by hurricane risk in the recent study of Kruttli et al. (2023). Each of these four sectors is highly plausible to be exposed to extreme weather risk. Utility firms can suffer from disruptions of transmission and distribution lines that result in revenue losses due to power outages as well as costly repairs (Hossain et al., 2021). 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 suffer from service interruptions due to extreme weather and 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 (Döhrmann et al., 2017). Table A2 of the Appendix provides examples from annual 10-K reports illustrating how companies from the aforementioned



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| **Panel A: Historically Affected Firms ($N$ = 1'459)** | | | | | |
|---|---|---|---|---|---|
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| 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: Unaffected Firms ($N$ = 2'089)** | | | | | |
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| 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 8: Portfolio Sorts for Historically Affected and Unaffected 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 period from January 1995 to December 2019. We differentiate between historically affected and unaffected firms. Affected 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. 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.



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four industries have been impacted by severe storms.

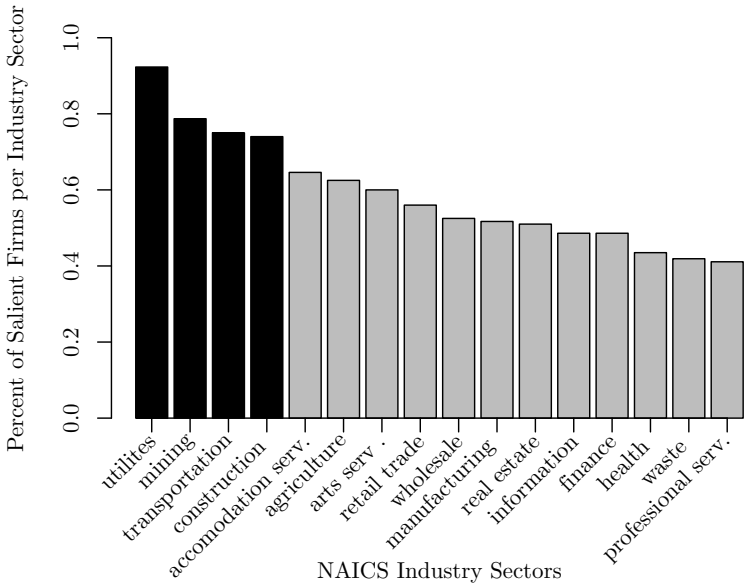



Figure 4: Percentage of Historically Affected Firms by Industry Sector

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

### *6.3. The Role of Institutional Share Holdings*

Does the extreme weather premium depend on the investor base holding the respective stocks? We shed light on this question when examining the price of extreme weather risk for equity that is held by a majority of institutional vs. retail investors. Motivation for this analysis is provided by Ilhan et al. (2020) who show that particularly institutional investors value climate risk disclosure of corporations and are potentially aware of a premium for extreme weather risk.

For the empirical analysis, we retrieve quarterly portfolio holding data of U.S.



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institutional investors from Thompson Reuters 13F. We merge this data with stock returns and firm characteristics from CRSP and Compustat. To perform asset pricing tests on a monthly basis, we apply the convention that portfolio holdings of institutions disclosed in quarter $t$ remain relevant for all three months within that quarter. For instance, 13F holdings disclosed in Q1 2018 are considered applicable for January, February, and March 2018.

For each month and stock, we compute the share of equity held by institutional and retail investors (calculated by 100% minus the share of equity held by institutions). We divide stocks into "high institutional ratio firms" (stocks that are classified in the top 20% of institutional ownership) and "low institutional ratio firms (stocks that are classified in the bottom 20% of institutional ownership and, hence, held mostly by retail investors). We then conduct univariate portfolios sorts for both subsamples and report results in Table 9. Our results reveal that in both subsamples there exist economically large risk-adjusted spreads of 0.516% for the high institutional ratio firms and 0.522% for the low institutional ratio firms. However, the spread is only statistically significant (at conventional levels) for the firms with high institutional investor share. Hence, our results are in line with the notion that the extreme weather risk premium is difficult to identify for retail investors and requires knowledge about climate uncertainty.



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| **Panel A: High Institutional Ratio Firms (Upper 20%)** | | | | | |
|---|---|---|---|---|---|
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| Portfolio 1 | −0.884 | +0.988% | 0.259% | 0.201% | 0.138% |
| 2 | −0.324 | +0.558% | −0.020% | −0.112% | −0.109% |
| 3 | −0.003 | +0.635% | −0.014% | −0.097% | −0.081% |
| 4 | +0.356 | +0.770% | 0.108% | 0.009% | −0.002% |
| Portfolio 5 | +1.074 | +0.501% | −0.276% | −0.347% | 0.373% |
| NMP (1−5) | | +0.487%* | +0.535%** | +0.548%** | +0.516%** |
| t-value | | (1.820) | (2.028) | (2.093) | (1.909) |

| **Panel B: Low Institutional Ratio Firms (Lowest 20%)** | | | | | |
|---|---|---|---|---|---|
| | $\beta_i^{LSLG}$ | Return | CAPM-$\alpha$ | FF3-$\alpha$ | Carhart-$\alpha$ |
| Portfolio 1 | −1.773 | −0.064% | −0.803% | −0.806% | −0.670% |
| 2 | −0.438 | +0.687% | 0.102% | 0.126% | 0.130% |
| 3 | +0.101 | +0.836% | 0.209% | 0.186% | 0.265% |
| 4 | +0.663 | +0.182% | −0.545% | −0.495% | −0.343% |
| Portfolio 5 | +1.949 | −0.499% | −1.385% | −0.347% | −0.331 |
| NMP (1−5) | | +0.436% | +0.582% | +0.492% | 0.522% |
| t-value | | (0.774) | (1.046) | (0.868) | (0.909) |

Table 9: Portfolio Sorts for Firms with High Institutional and Low Exposure

This table shows the out-of-sample portfolio sorts for firms with high institutional exposure (upper part) and low institutional exposure (lower part) in the time period between January 1995 to December 2019. The sample split is based on the quarterly institutional holdings ratio. 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.



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## 7. Summary and Conclusion

In this paper, we investigate the impact of extreme weather risk on the cross-section of stock returns. This risk premium can be motivated by different theoretical considerations, such as salience, loss cascades in production networks, market segmentation, as well as limited risk-sharing in a consumption-based framework.

We empirically test model predictions based on a dataset of US domestic firms from January 1995 to December 2009. To proxy for firms' extreme weather exposure, we compute their *LSLG* betas to US log storm loss growth. We then show that low *LSLG* beta stocks earn higher future returns than high *LSLG* beta stocks, delivering a risk-adjusted portfolio spread of more than 6% per annum. This premium can neither be explained by asset pricing risk factors nor firm characteristics, and withstands are variety of robustness tests.

Moreover, we examine the origin and magnitude of the extreme weather risk premium. Our results reveal that the premium is existent for geographically exposed and historically affected firms, i.e., those that mention weather risk related keywords in their past financial statements. We also break down the set of affected firms across industries and find that those in utilities, mining, transportation and construction are most vulnerable.

This study uncovers a new economic channel through which atmospheric natural disaster risk feeds into financial markets. Our findings suggest that extreme weather risk impacts exposed firms' cost of equity relative to their unexposed peers. As climate change will exacerbate weather risk, it is likely that the premium demanded by investors will persist and even increase in the future. The question how companies should react to this kind of climate risk exposure is an interesting topic for future research.



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## Appendix

*Theoretical Foundation in Consumption-Based Asset Pricing*

We assume investor heterogeneity and 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 various types of natural disaster risk is largely unavailable or unaffordable.[24] Accordingly, empirical evidence rejects the full consumption insurance hypothesis in this context (see, e.g., Sawada & Shimizutani, 2007).

Severe convective storms can inflict major losses on households and businesses through a variety of economic channels such as direct damage to physical assets as well as disruptions of supply chains, transmission and distribution lines, sales activities, and utility lifelines (Vilier et al., 2014; Hallegatte, 2015). Wind, extreme precipitation, and the resulting widespread flooding of urban agglomerations are the major loss drivers (see, e.g., Larsen, 2016; Wing et al., 2020). 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).[25]

We base our theoretical framework on the model of Constantinides & Duffie (1996). Assume that consumers exhibit homogeneous preferences, but heterogeneous consumption (income) processes that are nonstationary and heteroskedastic.[26] Markets are arbitrage-free and consumption comprises labor income plus investment proceeds. The model's main asset pricing implications are reflected

[24]The reluctance of insurance companies to provide coverage can be attributed to capitalization frictions and non-diversification 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, disaster protection gaps remain substantial (Holzheu & Turner, 2018).

[25]Munich Re estimates that only 5% of U.S. homeowners are insured against flood losses.

[26]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.



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by the following Euler equation (see Constantinides & Duffie, 1996):

$$\mathbb{E}_t[\tilde{R}^e_{t+1}] \quad = \quad -\frac{cov_t[\tilde{H}_{t+1}, \tilde{R}^e_{t+1}]}{\mathbb{E}_t[\tilde{H}_{t+1}]}, \tag{2}$$

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

$$\tilde{H}_{t+1} = \beta \left( \frac{\tilde{C}_{t+1}}{C_t} \right)^{-\alpha} \exp\left( \frac{\alpha\,(\alpha+1)}{2} \tilde{\gamma}^2_{t+1} \right). \tag{3}$$

Here, $\alpha$ equals the RRA coefficient[27], $\beta$ 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. (2) 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 (3) reflects the heterogeneous agents' dislike towards uninsurable idiosyncratic consumption risk. For homogeneous consumers, $\tilde{\gamma}^2_{t+1} = 0$ so that (2) reduces to the Euler equation of the standard representative-investor consumption-based model.

Through (3), the RRA coefficient $\alpha$ enters the covariance in (2), which hampers an empirical estimation of the model. Therefore, we draw on the extended Stein's Lemma introduced by Söderlind (2009) to analytically isolate $\alpha$:

*Assume that (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,*

[27]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 $u'(C_t) = C_t^{-\alpha}$



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$cov[\tilde{x}, h(\tilde{y})] = \mathbb{E}[h'(\tilde{y})] \cdot cov[\tilde{x}, \tilde{y}]$.

Given the log SDF is Gaussian, we can proceed as follows. Recognizing that $\tilde{x} = \tilde{R}^e_{t+1}$, $\tilde{y} = \ln(\tilde{H}_{t+1})$, and $h(\cdot) = \exp(\cdot)$, we may decompose the covariance $cov_t[\tilde{H}_{t+1}, \tilde{R}^e_{t+1}]$ in (2) as follows:

$$cov_t[\tilde{H}_{t+1}, \tilde{R}^e_{t+1}] = \mathbb{E}_t[\tilde{H}_{t+1}] \cdot cov_t[\tilde{h}_{t+1}, \tilde{R}^e_{t+1}], \tag{4}$$

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:

$$\tilde{h}_{t+1} = \ln(\beta) - \alpha\Delta\tilde{c}_{t+1} + \frac{\alpha(\alpha+1)}{2}\tilde{\gamma}^2_{t+1}, \tag{5}$$

which implies

$$cov_t[\tilde{h}_{t+1}, \tilde{R}^e_{t+1}] = -\alpha \cdot cov_t[\Delta\tilde{c}_{t+1}, \tilde{R}^e_{t+1}] + \frac{\alpha(\alpha+1)}{2} \cdot cov_t[\tilde{\gamma}^2_{t+1}, \tilde{R}^e_{t+1}]. \tag{6}$$

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 (4) and (6), we may restate the risk premium (2) as follows:

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

In addition to the variables of the classical representative investor model included in the first summand of (7), 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,



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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 (7) as follows:[28]

$$\begin{aligned}\mathbb{E}_t[\tilde{R}^e_{t+1}] &= \Big(\rho_t[\Delta\tilde{c}_{t+1}, \Delta\tilde{l}_{t+1}] \cdot \rho_t[\tilde{R}^e_{t+1}, \Delta\tilde{l}_{t+1}] + \mathbb{E}_t[\Delta\tilde{c}^*_{t+1}\tilde{R}^{e*}_{t+1}]\Big) \cdot \alpha \\ &- \Big(\rho_t[\tilde{\gamma}^2_{t+1}, \Delta\tilde{l}_{t+1}] \cdot \rho_t[\tilde{R}^e_{t+1}, \Delta\tilde{l}_{t+1}] + \mathbb{E}_t[\Delta\tilde{\gamma}^{*2}_{t+1}\tilde{R}^{e*}_{t+1}]\Big) \cdot \frac{\alpha(\alpha+1)}{2}. \quad (8)\end{aligned}$$

$\tilde{c}^*_{t+1}$, $\tilde{R}^{e*}_{t+1}$ 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 $\Delta\tilde{l}_{t+1}$.[29] Equation (8) predicts an extreme weather 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.

Equation (8) allows for an empirical verification in two steps: For an extreme weather risk premium to arise, we need:

i. *LSLG* to be negatively correlated with log consumption growth and/or positively correlated with consumption inequality and
ii. *LSLG* to be negatively correlated with excess returns on the risky asset.

*Decomposing Correlations*

This part of the Appendix contains the formal details behind the decomposition of the correlations in Equation (7) required for Equation 8. 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

[28]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 next Section. 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 $Z = \tilde{R}^e_{t+1}$.

[29]Note that (8) does no longer contain standard deviations, because the variables have been standardized.



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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 $Y$ ($\rho[Z, Y]$):

$$a = \mathbb{E}[XY] = \frac{\mathbb{E}[XY]}{\sqrt{\mathbb{E}[X^2] \cdot \mathbb{E}[Y^2]}} = \rho[X, Y], \tag{13}$$

$$b = \mathbb{E}[ZY] = \frac{\mathbb{E}[ZY]}{\sqrt{\mathbb{E}[Z^2] \cdot \mathbb{E}[Y^2]}} = \rho[Z, Y]. \tag{14}$$



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

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

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

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 $Z^*$ ($\mathbb{E}[Z^{*2}]$):

$$\mathbb{E}[X^{*2}] = 1 - \rho[X, Y]^2, \tag{17}$$

$$\mathbb{E}[Z^{*2}] = 1 - \rho[Z, Y]^2. \tag{18}$$

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 $\rho[Z, Y]$:

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

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 $\mathbb{E}[X^*Z^*]$.



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Dissecting the latter by means of $cov\left[X^*, Z^*\right] = \mathbb{E}\left[X^* Z^*\right] - \mathbb{E}\left[X^*\right] \cdot \mathbb{E}\left[Z^*\right]$ yields:

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

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 $(\rho[X^*, Z^*]) = -1$.

*Extreme Weather Risk and Macroeconomic Fundamentals*

To test the empirical implications of the theory in Section 7, we merge data from several sources. We estimate $\Delta\tilde{c}$ from per capita non-durable goods and service consumption expenditures in the U.S. and $\tilde{\gamma}^2$ as the state-level cross-sectional variance of log income growth. Note that income inequality is a common measure for consumption inequality (see, e.g., Attanasio & Pistaferri, 2016; Chen & Yang, 2019). 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. Finally, we estimate $\Delta\tilde{l}$, i.e., *LSLG* based on the SHELDUS inflation-adjusted thunderstorm loss data (per capita) that also underpins our main analyses (see Figure 5). To match the frequency of the consumption data, we 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)

In line with our theoretical framework, we 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 1995. Table A1 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 period from January 1995 to December 2019.[30]

[30]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.



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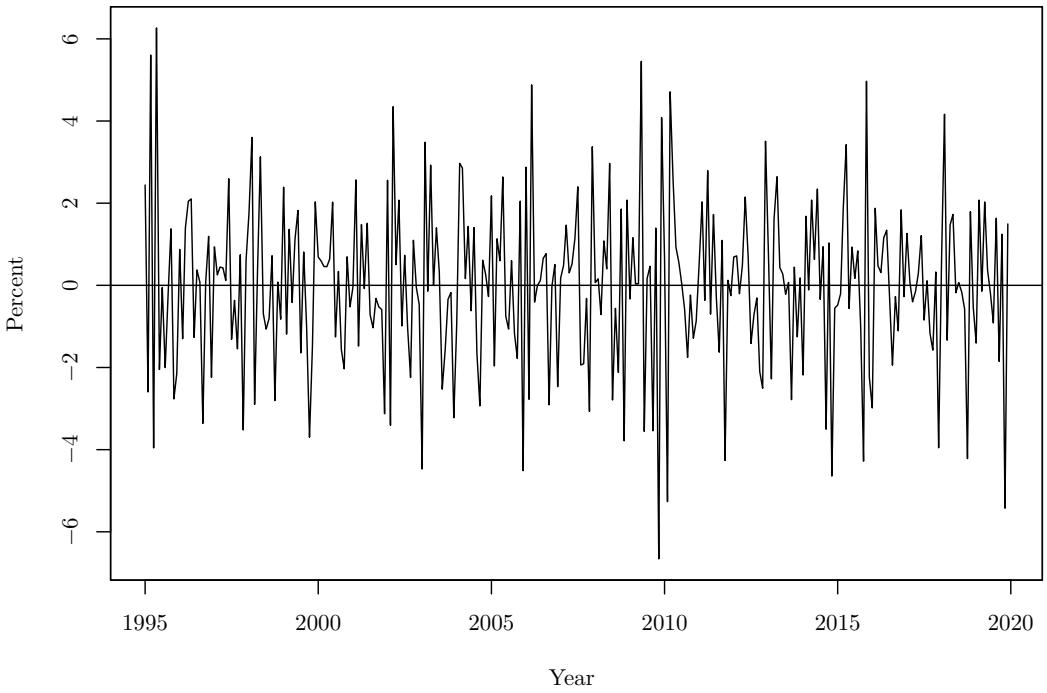



Figure 5: Log Storm Loss Growth

This figure displays the evolution of the log storm loss growth per capita ($LSLG$) for the United States based on inflation-adjusted (2009 U.S. dollars) thunderstorm loss data (per capita) from the Spatial Hazard Events and Losses Database (SHELDUS).

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).[31] 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%

[31] 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).



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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.

| **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 A1: Descriptive Statistics and Correlations for LSLG 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 $\rho[\tilde{\gamma}^2, \Delta\tilde{l}]$.



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*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 A2: Anecdotal Evidence for the Impact of Severe Convective Storm Risk on Firms



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