Hurricane Risk and Asset Prices

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Abstract

We examine hurricane exposure as a systematic risk factor in the US stock market. Motivated by a consumption-based asset pricing model with heterogeneous agents, we derive a necessary and sufficient condition for a hurricane risk premium in the cross-section of stock returns. Empirically, we find that – in the period from 1995 to 2020 – stocks that react negatively to aggregate hurricane losses outperform stocks that react positively by almost 9% p.a. The hurricane premium is not explained by standard asset pricing risk factors nor stock characteristics. Our results emphasize the importance of climate risk for firms' cost of capital.

Keywords: Hurricane Risk, Consumption-Based Asset Pricing with Heterogeneous Agents, Empirical Asset Pricing, Climate Change
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> *"We cannot quantify the exact effects climate change has on weather related catastrophes, but it is clear that climate change is a systemic risk to the global macroeconomy."*
>
> **Jerome-Jean Haegeli**,
> Group Chief Economist at Swiss Re

1. Introduction

The economic repercussions of natural disasters have become increasingly severe. Ongoing population growth, urban sprawl into hazard-prone areas (such as coastlines, flood plains, or tectonic faults) 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: in the three years 2017, 2018, and 2019, natural catastrophes caused combined economic damages of about USD 600 billion around the world (Swiss Re, 2020), more than the annual GDP of Sweden.[1] Weather-related perils, such as cyclones and floods, have increased threefold since the 1980s and are responsible for the lion's share of global disaster losses (Hoeppe, 2016).[2] The most violent type of natural hazard faced by households and businesses in the U.S. are Atlantic hurricanes, which account for eight of the ten costliest disasters in the history of the country.[3] Hurricane risk is highly dynamic, because hurricane activity exhibits seasonality and varies with the North Atlantic sea surface temperature (SST) on interannual and decadal time scales (Kossin & Vimont, 2007; Smith et al., 2010; Hallam et al., 2019). The last three decades were the hottest ever measured (Sippel et al., 2020). Thus, unsurprisingly, these periods also set new records with regard to extreme hurricane events[4] and their economic impacts.[5]

Against this background, we study whether hurricane activity has become a systematic risk factor in the financial markets. We focus on hurricane risk over other natural perils, because

[1] The World Bank reports Sweden's GDP in 2019 at around USD 530 bn.

[2] The frequency of geophysical events, in contrast, has remained largely constant.

[3] See Insurance Information Institute: Facts + Statistics: U.S. catastrophes.

[4] Sandy (2012) was the largest hurricane ever observed in the Atlantic. Harvey (2017) offloaded the largest quantity of rain in US history. Ophelia (2017) formed furthest northeast of all known category 3 hurricanes. Irma (2017) sustained wind speeds of 300 kilometers per hour longer than any other storm before it.

[5] Seven of the ten costliest disasters between 2010 and 2019 were hurricanes (see to Statista.com).

it is geographically widespread, economically severe and follows clear patterns over time. To predict the existence of a hurricane risk premium, we propose a theoretical framework rooted in consumption-based asset pricing. Specifically, we build on the model of Constantinides & Duffie (1996) with heterogeneous agents subject to idiosyncratic consumption shocks, for which hurricanes are a prime example. The major protection gaps among U.S. households and businesses with regard to hurricane losses (in particular flood-related ones) warrant the assumption that risk sharing in the economy is strictly limited. First, we modify the original model by means of the extended Stein's Lemma (see Söderlind, 2009). This allows us to decompose the expected excess return for risky assets into two components. The first one is governed by the correlation of an asset's excess return with aggregate consumption growth. The second one depends on the correlation between the asset's excess return and the cross-sectional variance of individual consumption growth. Subsequently, we advance the model into a theory for the risk premium on hurricane-sensitive assets. To this end, we further decompose the expected excess return into i) correlations between macroeconomic fundamentals (consumption growth; consumption inequality) and aggregate hurricane loss growth (AHLG) as well as ii) the correlation between the excess returns on risky assets and AHLG. This decomposition allows us to pursue an identification strategy in two steps, evaluating both a necessary and a sufficient condition for a hurricane risk premium.

Our empirical analyses start with the correlations between macroeconomic fundamentals and AHLG. We compute AHLG (per capita) from a long-term data set of real U.S. hurricane losses published by Weinkle et al. (2018), spanning the period from 1900 to 2017. In addition, we use unfiltered non-durable goods and services consumption data (per capita) from Kroencke (2017), which is available for the years 1928 to 2018, and state-level income data (per capita) from the Bureau of Economic Analysis (BEA), which spans the time period between 1948 and 2019. We draw on the latter to estimate consumption inequality. It turns out that there is no statistically significant long-run correlation between aggregate consumption growth and AHLG. However, we do find AHLG to be significantly positively correlated with the variance of state-level income growth from the mid 1990s onward. Since then individuals were thus confronted with large AHLG rates at times when consumption inequality and thus marginal utility was high. This provides necessary (but not sufficient) evidence for the emergence of hurricanes as a fundamental economic risk factor during the last 25 years.

Next, we examine the existence of a hurricane risk premium as well as its size and dynamics through a set of established asset pricing tests on all common U.S. stocks in the CRSP database between January 1963 and December 2020. We begin with univariate sorting (value and equally-weighted) based on the stocks' betas with regard to AHLG. As our hurricane loss data is recorded on an annual scale, we follow Adrian et al. (2014) and Chen & Yang (2019) in constructing a factor mimicking portfolio based on the 25 size and book-to-market sorted Fama-French test assets. The factor mimicking portfolio allows us to run all subsequent analyses with monthly excess return time series. For each stock, we then estimate a time-varying beta with regard to the AHLG mimicking portfolio by means of 60-month rolling regressions. We use these AHLG betas to assign the stocks to quintile portfolios in every month. Depending on their business model, their exposure and a storm's landfall location, firms can both suffer or benefit from the occurrence of a hurricane.[6] These opposing economic consequences are captured by their AHLG beta. Stocks with negative AHLG betas exhibit low returns when hurricane loss growth is high. They should therefore carry a risk premium over stocks with positive AHLG betas.

Indeed, we find that the average monthly excess return monotonically increases from the portfolio with the largest positive average AHLG beta to the portfolio with the largest negative average AHLG beta. Consistent with our theory and the empirically-documented correlation between AHLG and income inequality, the effect is driven by the last two and a half decades in the sample. The exact same time period is characterized by abnormally warm sea surface temperatures in the North Atlantic and a scientifically-documented surge in hurricane activity (Goldenberg et al., 2001; Klotzbach & Gray, 2008). The effect is highly significant and large: between 1995 and 2020, a zero-investment portfolio of stocks with negative minus positive hurricane risk sensitivity (NMP), as measured by the AHLG beta, earned an average excess return of 0.74 percent per month (8.85 percent p.a.), with a t-statistic of 3.79. The largest part of this spread withstands an adjustment for risk exposure to the Capital Asset Pricing Model (CAPM), the Fama & French (1992) three-factor, and the Carhart (1997) four-factor model. Moreover, the outcome is robust across two alternative measurements of AHLG.[7]

We continue with multivariate analyses. Fama & MacBeth (1973) regressions show that the effect of the AHLG betas stays statistically and economically strong when we control for firm-specific characteristics, such as market beta, size, idiosyncratic volatility and coskewness.

[6] Construction firms, for example, may experience a demand surge effect as the demand for skilled labour increases in the aftermath of severe natural disasters (see, for example, Döhrmann et al., 2017).

[7] In addition to the Weinkle et al. (2018) data set, we use hurricane losses from EM-DAT, and the excess returns on a portfolio of single-peril US Windstorm catastrophe bonds.

Subsequently, we turn our attention to the time series and cross-sectional properties of the zero-investment portfolio NMP. First, we regress its monthly time series of excess returns on a broad battery of ten alternative factor models.[8] All of them leave us with large significant positive alphas of at least 0.505 percent per month (6.06 percent p.a.). Second, we show that adding NMP to the Fama & French (1992) three-factor model as well to its extension with the Carhart (1997) momentum factor, substantially reduces pricing errors in the cross section of 25 test portfolios sorted by size and hurricane risk sensitivity.

In the next step, we inspect the economic mechanism behind the hurricane risk premium. As firms can exhibit close economic links (Cohen & Frazzini, 2008) and shocks from natural disasters are known to strongly propagate in production networks (Barrot & Sauvagnat, 2016), we rely on textual analysis of public financial statements rather than the geographic location of establishments for the identification of hurricane risk exposures. Following Cohen et al. (2020), we download all complete 10-K, 10-K405 and 10-KSB filings from the EDGAR website of the U.S. Securities and Exchange Commission (SEC), which covers the time period from 2000 to 2017. We then match them with the stock market data from CRSP and the accounting information from Compustat. Using this combined sample, we search for firms that mentioned the keyword *hurricane loss* at least once in in their financial statements and identify the states in which they are incorporated. This allows us to split the sample in two parts: states in which at least one headquartered firm was actually impacted by a hurricane and those in which no such incidents were reported. In doing so, we are able to map economic hurricane risk exposure into a geographic pattern. By repeating the univariate sorting for these two subsamples, the risk premium can be attributed to the states that are economically (not just geographically) exposed to hurricane risk. The other subsample, in contrast, shows no significant effect.

Another important aspect of the economic mechanism is the time varying nature of hurricane risk. Specifically, hurricane occurrence frequencies are not constant throughout the year. Instead, most activity is concentrated in the Atlantic hurricane season from June to November, with the risk peaking in the third quarter (see, e.g., Goldenberg et al., 2001). We exploit

[8] Those are the Fama & French (1992) and Carhart (1997) models 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 (orthogonalized), the Frazzini & Pedersen (2014) betting-against-beta factor, the Fama-French short- and long-term reversal factors, the Fama & French (2015) operating profitability and investment factors, as well as the investment and profitability factors Hou et al. (2014)

this strong time series pattern for identification. First, we show graphically that the average quarterly excess returns of NMP are inversely related to hurricane occurrence frequencies. A time series regression of NMP on dummy variables for quarters two to four provides evidence for a significantly lower excess return in the third quarter compared to the first quarter. Next, we filter out the noise in the quarterly NMP series by means of a three-quarter rolling mean and examine autocorrelation function (ACF), partial autocorrelation function (PACF) and periodogram. All three diagnostics point to a seasonal first-order autogregressive process, which we confirm by fitting an ARIMA(1,0,2)$(1,0,0)_4$ model. The significant coefficient for the first-order seasonal autoregressive process provides further conclusive evidence for an annually repeating pattern consistent with the underlying hurricane risk itself.

We also determine to which extent the hurricane risk premium varies across firm size. To this end, we run double sorts. We first sort all stocks in a given month on their average market capitalisation over the preceding 60 months. Within the resulting market capitalization quintiles, we then sort the stocks into five portfolios based on hurricane beta. We can confirm the hurricane risk premium for medium-sized and larger firms, but not for the smallest 40 percent of firms. We attribute this finding to the lesser economic links among the latter.

Finally, we examine the hurricane risk premium by industry. To this end, we split our sample along SIC divisions and separately sort on hurricane risk beta in each subsample. We find significant hurricane risk premiums for four out of ten industry divisions: construction, manufacturing, services, as well as finance, insurance and estate. This is consistent with earlier results in the literature, documenting that hurricane risk may affect firms via direct exposures, supply chain disruptions, revenue drops, order book effects, and labor market reactions.

Our results have a whole number of important implications. First, we unveil a novel transmission channel through which extreme weather events unfold a major economic impact. Second, a natural disaster risk that used to be unrelated to financial risks has become a systematic factor. Hence, insurance markets, which historically enabled the sharing of such risks throughout the economy, are potentially converging to the broader capital markets much faster than previously thought. Third, firms that are threatened by hurricane risk, either directly or through close economic links, nowadays exhibit a higher cost of equity than their unexposed peers. Many of these firms already pay higher insurance premiums for the coverage of their physically-exposed property. An elevated cost of equity exacerbates this issue and may thus have a major impact on future business decisions such as the geographical location of establishments or the selection of suppliers. Fourth, in the face of climate change, economic integration, and an ever-increasing concentration of production factors in coastal regions, the impact of hurricane risk can be expected to rise even further, making it likely that the premium will persist in the long run.[9]

The remainder of this paper is organized as follows. In Section 2, we review the related literature. Section 3 lays the theoretical foundation for the hurricane risk premium in form of an extended consumption-based asset pricing model with heterogeneous agents subject to individual consumption shocks. In Section 4, we then discuss the systematic properties of hurricane risk, estimate AHLG and test the empirical correlations between AHLG as well as consumption growth and consumption inequality, respectively. Section 5 contains the main asset pricing tests, including the construction of the AHLG mimicking portfolio, univariate sorting on AHLG betas, multivariate Fama & MacBeth (1973) regressions, robustness tests with regard to different measurements of hurricane losses, time series regressions on a broad range of established factor models, and an analysis of the cross-sectional pricing fit for 25 test portfolios sorted by size and momentum. In the penultimate Section 6, we further explore the economic mechanism behind our empirical results, mapping firm's economic hurricane exposure into a geographic pattern. Finally, in Section 7, we summarize our findings and draw our conclusion.

2. Related Literature

Our work directly contributes to a growing literature on the links between natural disasters and financial markets. Aspects covered so far include the immediate response of stock returns for local firms (Shan & Gong, 2012; Bourdeau-Brien & Kryzanowski, 2017; Seetharam, 2017), potential stock market reactions to trillion-dollar catastrophes (Mahalingam et al., 2018), as well as the impact of the uncertainty caused by impending hurricanes on option-implied volatilities of exposed firms (Kruttli et al., 2019) and on market liquidity (Rehse et al., 2019).[10] To the best of our knowledge, there is very little research to date that examines the asset pricing implications of natural disasters in general and of hurricane risk in particular. This is surprising, given the wide array of economic repercussions documented for such extreme events. Two exceptions are Hong et al. (2019) and Lanfear et al. (2019). The former search for a drought risk premium in the stock returns of food companies, whereas the latter provide evidence that the well-known

[9]See NOAA Global Warming and Hurricanes: An Overview of Current Research Results for an extrapolation of hurricane risk in the 21st century.

[10]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).

book-to-market equity and momentum factors are sensitive to hurricane risk.

Moreover, we add to the thriving research stream on the economics of natural disasters.[11] Extant studies in this field have considered the impact on growth (Strobl, 2011; Cavallo et al., 2013; Felbermayr & Gröschl, 2014), consumption (Sawada & Shimizutani, 2008; Aladangady et al., 2017), income (Miljkovic & Miljkovic, 2014), firm sales (Addoum et al., 2020), and local labor markets (Belasen & Polachek, 2008; McIntosh, 2008). Further studies have focused on post-disaster recovery effects (Döhrmann et al., 2017; del Valle et al., 2020), major implications of NatCat risk for policymakers (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 (Stern, 2008; Custodio et al., 2021).

Given the latter thought, this paper evidently also contributes to the to the rapidly expanding climate finance literature, which has previously concentrated on the questions whether regulatory uncertainty and carbon risk are priced in option and stock markets (Braun et al., 2019c; Ilhan et al., 2020; Ardia et al., 2020; Bolton & Kacperczyk, 2021a,b; Sautner et al., 2021), what impact climate change could have on asset values (Dietz et al., 2016), and how climate risks can be hedged (Baker et al., 2020; Andersson et al., 2016; Engle et al., 2020). In addition, our findings are linked to recent work on the importance of climate risks for institutional investors (Roth Tran, 2019; Krueger et al., 2020) and firms' access to capital (Schüwer et al., 2019).

Our paper also speaks to the emerging literature on asset pricing for insurance risks that originated from studies of coupon and yield spreads in markets for catastrophe bonds (Braun, 2016; Gürtler et al., 2016). Related studies in this area examined how NatCat exposure impacts the cost of capital of insurance companies (Ben Ammar et al., 2018; Barinov et al., 2020), the implied volatilities of options on insurer stocks (Ben Ammar, 2020), and the expected excess returns on funds specializing in investable insurance risk (Braun et al., 2019b). Further relevant work analyzed severe NatCat risk in the context of consumption-based asset pricing models (Dieckmann, 2019; Braun et al., 2019a). Most recently, scholars in this area have begun to consider implied event probabilities for valuation and the prediction of seasonality (Beer & Braun, 2021; Herrmann & Hibbeln, 2021).

Finally, our results enrich a particular stream of the general asset pricing literature, which incorporates rare disasters into representative investor consumption-based models to explain the historically-observed equity premium (Rietz, 1988; Barro, 2006; Berkman et al., 2011; Gabaix,

[11] For a comprehensive overview of this literature, refer to Kousky (2014) and Botzen et al. (2019).

2012; Wachter, 2013). While these studies focus on political and economic events, such as wars and recessions, anecdotal evidence indicates that the most extreme natural disasters may lead to a severe economic contractions, too.[12] Due to their extraordinarily long recurrence periods, however, the impact of such mega catastrophes on asset prices is hard to measure empirically. We focus on annually recurring hurricane risk that may not be extreme enough to enter into the marginal utility of the representative investor, but can increase consumption heterogeneity in the economy.

3. Theoretical Foundation

Our theory for the hurricane risk premium builds on consumption-based asset pricing with heterogeneous agents subject to idiosyncratic consumption shocks (Mankiw, 1986; Weil, 1992; Heaton & Lucas, 1996; Constantinides & Duffie, 1996; Gomes & Michaelides, 2011). Hurricanes are a prime example for an aggregate shock that does not spread equally throughout the economy. *Ex ante* a large fraction of households and businesses are exposed. *Ex post*, however, the consumption loss is concentrated among a few. Hurricanes can have direct and indirect impacts on households and businesses. Even without direct damage to physical assets, there are a variety of economic channels such as disruptions of production networks, supply chains, purchase and sales activities, and utility lifelines, through which hurricane risk may hit far beyond the region immediately affected by the event (Hallegatte, 2015).

Apart from consumer heterogeneity, we assume incomplete consumption insurance, implying that there are no contingent-claims markets that allow for full risk sharing among the heterogeneous agents in the economy (Mankiw, 1986). This is a reasonable conjecture, because insurance against large-scale natural disaster risk is often unavailable or unaffordable. Accordingly, empirical evidence rejects the consumption insurance hypothesis in the context of large-scale natural disasters (Sawada & Shimizutani, 2007). The reluctance of insurance companies to provide widespread coverage has, among others, been explained by high capital requirements, market imperfections, and nondiversification traps (Jaffee & Russell, 1997; Froot, 2001;

[12] 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 stock market crash in 1907 (Odell & Weidenmier, 2004).

Ibragimov et al., 2009).[13] With regard to hurricanes, storm surge and extreme precipitation pose a major problem, as they overburden sewage systems and result in widespread flooding of urban agglomerations. Despite the availability of subsidized coverage from the National Flood Insurance Program (NFIP), only five percent of homeowners are insured against such direct flood losses.[14] In addition to such direct consequences, large-scale flooding events are known to inflict serious business interruption losses on the economy (Vilier et al., 2014).

We start with the model of Constantinides & Duffie (1996). Assume that consumers exhibit homogeneous preferences, but heterogeneous consumption (income) processes that are nonstationary and heteroskedastic.[15] 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:

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

where $\tilde{R}^e_{t+1}$ represents the excess return of a risky asset and $\tilde{H}_{t+1}$ denotes the stochastic discount factor (SDF) or pricing kernel. With constant relative risk aversion (CRRA) represented by the power utility function over time-t consumption C_t, the pricing kernel $\tilde{H}_{t+1}$ 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[16], β is the subjective time-discount factor, and $\tilde{\gamma}^2_{t+1}$ is the variance of the cross-sectional distribution of individual consumption growth (income inequality). An asset carries a risk premium, if individuals expect its future excess returns to exhibit a negative covariance with $\tilde{H}_{t+1}$. For homogeneous consumers, $\tilde{\gamma}^2_{t+1} = 0$ so that (1) reduces to

[13] 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).

[14] See Munich Re (2020): The flood insurance gap in the United States.

[15] 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.

[16] Since $u(C_t) = \frac{C_t^{1-\alpha}}{1-\alpha}$, for $\alpha \to 1$, we have $u(C_t) = \ln(C_t)$. Note that, since the elasticity of intertemporal substitution ψ is the reciprocal of the RRA coefficient α, the standard power utility function does not allow for a disentanglement of time and risk preferences. The marginal utility is $u'(C_t) = C_t^{-\alpha}$

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 $\mathrm{E}[|h'(\tilde{y})|] < \infty$. *Then,* $cov[\tilde{x}, h(\tilde{y})] = \mathrm{E}[h'(\tilde{y})] \cdot cov[\tilde{x}, \tilde{y}]$.

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 (1) as follows:

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

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

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

The second covariance on the right hand side will be nonzero, if the cross-sectional variance of individual consumption growth 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:

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

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 aggregate consumption growth and negatively correlate with consumption inequality. Both implications are empirically testable.

Next, we interlace hurricane risk as a fundamental economic risk factor. To this end, let $\Delta a\tilde{h}l_{t+1} = \ln(\mathrm{A\tilde{H}L}_{t+1}/\mathrm{A\tilde{H}L}_t)$ be log AHLG, with $\mathrm{A\tilde{H}L}_t$ denoting aggregate hurricane 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 $\Delta a\tilde{h}l_{t+1}$. This allows us to decompose the correlations in (6) as follows:[17]

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

$\tilde{c}^*_{t+1}$, $\tilde{R}^{e*}_{t+1}$ 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 $\Delta a\tilde{h}l_{t+1}$.[18] Equation (7) predicts a hurricane risk premium based on expected correlations between macroeconomic fundamentals and AHLG ($\rho_t[\Delta\tilde{c}_{t+1}, a\tilde{h}l_{t+1}]$, $\rho_t[\tilde{\gamma}^2_{t+1}, \Delta a\tilde{h}l_{t+1}]$) as well as the excess return on a risky asset and AHLG ($\rho_t[\tilde{R}^e_{t+1}, \Delta a\tilde{h}l_{t+1}]$). Using the law of iterated expectations, it can be shown that this equation also holds for unconditional moments. This allows us to separate the empirical verification of the theory into two steps, evaluating both a necessary and a sufficient condition. More specifically, for a hurricane risk premium to arise, we need i) AHLG to be (negatively) correlated with aggregate consumption growth and/or (positively) correlated with consumption inequality and ii) AHLG to be negatively correlated with the excess return on the risky asset.

[17]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 (23) with $X = \Delta\tilde{c}_{t+1}$ and $X = \tilde{\gamma}^2_{t+1}$, respectively, as well as $Y = \Delta a\tilde{h}l_{t+1}$ and $Z = \tilde{R}^e_{t+1}$

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

4. Hurricane Risk

4.1. Systematic Properties

Hurricane risk is severe[19] and not locally contained, making it a plausible systematic risk factor. Judging by hurricane occurrences since the mid 19th century, every county along the U.S. East Coast and Gulf Coast is exposed (Zeng et al., 2009). Hurricane Katrina alone, the single most expensive natural disaster in American history, caused losses across six states.[20] Taking into account the ever-growing integration of economies through firm-linkages and production networks (Cohen & Frazzini, 2008; Barrot & Sauvagnat, 2016), it is clear that hurricanes can cause losses to businesses geographically far away from their landfall location. Hurricanes are also known to impact firms through management reactions (Dessaint & Matray, 2017), cash flow shocks (Brown et al., 2021), reallocation of capital (Cortés & Strahan, 2017), and credit constraints (Collier et al., 2020). There are even immediate connections between hurricane risk and stock markets through overreactions of fund managers and fire sales by hurricane-struck investors with spontaneous liquidity needs (Tubaldi, 2021; Alok et al., 2020).

In addition, hurricane risk follows clear patterns over time, an important property that can be exploited for identification. Specifically, hurricane activity exhibits seasonality and varies with the North Atlantic sea surface temperature (SST) on interannual and decadal time scales (Kossin & Vimont, 2007; Smith et al., 2010; Hallam et al., 2019).[21] Research indicates that, after a time of subdued hurricane risk in the 1970s and 1980s, we have been in an active period since 1995 (Goldenberg et al., 2001; Klotzbach & Gray, 2008). The scientific concept of hurricane activity comprises frequency, duration and intensity of storms (Kossin & Vimont, 2007).[22] Extreme hurricanes are more frequent in active periods compared to quiet periods (Donnelly & Woodruff, 2007). Intensity is also higher: the number of events with hurricane-force winds stronger than 200 kilometers (250 kilometers) per hour have doubled (tripled) compared to the 1980s (Kossin, 2018). Finally, hurricane decay speed has declined so that storm systems last longer and wreak havoc further inland (Li & Chakraborty, 2020; Chavas & Chen, 2020).

[19]Hurricanes account for the by far largest fraction of natural disaster losses in the U.S. (Swiss Re, 2019).

[20]See Insurance Information Institute: Hurricane Katrina: The Five Year Anniversary.

[21]The climate phenomena behind these variations are the El Niño Southern Oscillation and the Atlantic Multidecadal Oscillation.

[22]Both duration and intensity are major drivers of a cyclone's destructiveness (Emanuel, 2005).

4.2. Measurement

To construct our hurricane risk factor, we use a long and complete dataset provided by Weinkle et al. (2018), consisting of 197 hurricanes in the continental U.S. from 1900 to 2017.[23] The main data includes the year and state of occurrence for each event, its rank on the Saffir-Simpson scale,[24] and the economic losses in contemporaneous US-Dollars. The data also includes economic losses normalized by means of the Pielke Landsea 2018 (PL18) and Collins Lowe 2018 (CL18) methodologies. Normalization is an important aspect in natural disaster research, because it adjusts the losses of historical events to present-day societal conditions. Thus, one may rule out inflation, increases in wealth, and population growth as loss drivers and compare the destructiveness of events across time. Finally, the following items are available on an occurrence-year and present-day basis: aggregate wealth, population in affected counties, population in the U.S., number of housing units in affected counties, number of housing units in the U.S., real wealth per capita, and real wealth per housing unit.

Figure 1 shows the PL18 normalized aggregate hurricane losses from 1977 to 2017 together with the smoothed Atlantic Multidecadal Oscillation (AMO) Index, published by NOAA. The AMO measures the SST variability in the North Atlantic on a decadal timescale. Evidently, the AMO switched into a warm phase after 1995. Scientific research shows that the same time period is characterized by a clear upward trend in Accumulated Cyclone Energy (ACE) and the Power Dissipation Index (PDI) (Villarini & Vecchi, 2012).[25] Moreover, the geographic region in which cyclones can form has expanded and the storms themselves are able to travel greater distances away from the topics, reaching previously unharmed locations (Lucas et al., 2014; Kossin et al., 2014). Thus, unsurprisingly, the average PL18 damage in the US jumped from USD 10.5 billion for the period from 1977 to 1994 to more than USD 23.5 billion between 1995 and 2017. Some of these developments may already be attributable to anthropogenic forcing rather beyond the usual cyclical patterns (Sobel et al., 2016). The onset of climate change will therefore further add to the significance of hurricane risk (Emanuel, 2005, 2017).

[23]We will confirm the robustness of all our main empirical results on additional hurricane loss datasets.

[24]Hurricanes are assigned a rank of one to five, based on their maximum sustained wind speed (see NOAA). Events of all five categories can cause storm surge and severe flooding. Major hurricanes in the categories 3 to 5 additionally deal catastrophic wind damage and may therefore lead to casualties.

[25]Both ACE and PDI are aggregates of intensity, frequency, and duration and therefore represent a concise metrics of hurricane activity over a whole season.

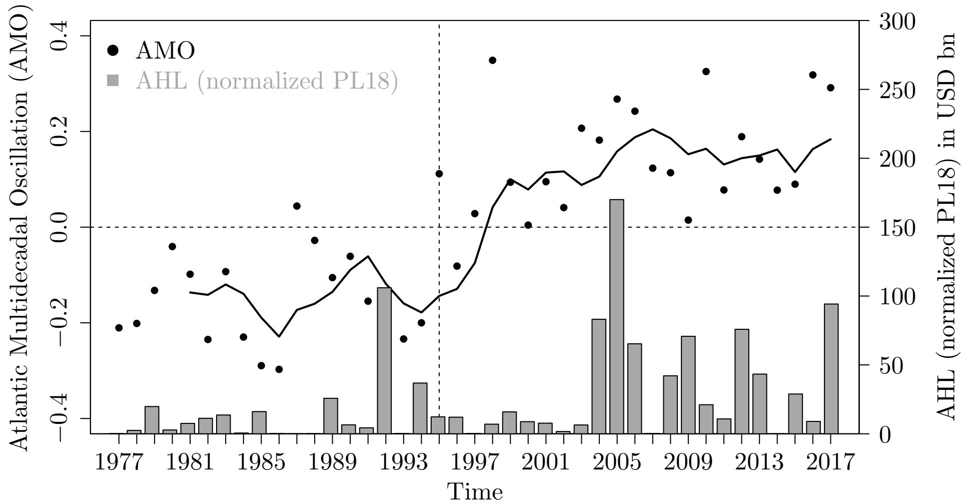

Figure 1: AMO and Aggregate Hurricane Losses (AHL)

This figure shows the Atlantic Multidecadal Oscillation (AMO) Index in °C (left axis) together with aggregate hurricane losses (AHL) from Weinkle et al. (2018) normalized based on the PL18 methodology (right axis). The black curve represents a four-year moving average of the AMO Index.

4.3. Correlations with Macroeconomic Fundamentals

In the following, we investigate the empirical correlations between log AHLG ($\Delta\tilde{ahl}$), log consumption growth ($\Delta\tilde{c}$), and consumption inequality ($\tilde{\gamma}^2$) as a necessary condition for a hurricane risk premium. All three variables are considered in real terms.[26] $\Delta\tilde{ahl}$ is calculated based on the Weinkle et al. (2018) aggregate hurricane losses (per capita). Moreover, we compute log consumption growth $\Delta\tilde{c}$ from unfiltered non-durable goods and services consumption data (per capita) provided by Kroencke (2017).[27] Finally, we estimate $\tilde{\gamma}^2$ by means of the state-level cross-sectional variance of income growth, using annual personal income statistics (per capita) from the BEA.[28] Table 1 shows a range of descriptive statistics for the aforementioned variables together with the relevant correlations for the time periods 1978−1994 and 1995−2017.

[26]We adjust nominal figures using the Consumer Price Index (CPI) (base year 2012).

[27]Kroencke (2017) argues that the National Income and Product Accounts (NIPA) consumption data are subject to measurement errors generated by time aggregation and filters.

[28]State-level consumption data is unavailable. Hence, measuring consumption inequality through income inequality is a common procedure in the asset pricing literature (see, for example, Chen & Yang, 2019) and beyond (see, for example, Attanasio & Pistaferri, 2016).

	distribution					correlations	
1978−1994	mean	median	s.d.	min.	max.	$\Delta\widetilde{ahl}$	p-val.
$\Delta\widetilde{ahl}$	0.325	0.581	3.639	−6.840	5.830	1.000	
$\Delta\tilde{c}$	1.918	1.249	2.494	−2.593	7.123	0.298	0.245
$\tilde{\gamma}^2$	0.142	0.114	0.084	0.038	0.337	−0.209	0.421
1995−2017	mean	median	s.d.	min.	max.	$\Delta\widetilde{ahl}$	p-val.
$\Delta\widetilde{ahl}$	0.087	−0.097	3.428	−8.194	8.163	1.000	
$\Delta\tilde{c}$	1.403	1.346	2.005	−2.944	4.717	0.001	0.995
$\tilde{\gamma}^2$	0.398	0.260	0.358	0.126	1.624	0.369	0.083*

Table 1: Descriptive Statistics and Correlations for AHLG and Macroeconomic Fundamentals

This table shows the mean, median, standard deviation (s.d.), minimum and maximum for the annual time series of log AHLG ($\Delta\widetilde{ahl}$), log consumption growth ($\Delta\tilde{c}$), and consumption inequality ($\tilde{\gamma}^2$). Moreover, it includes empirical estimates for the correlations $\rho[\Delta\tilde{c}, \Delta\widetilde{ahl}]$ and $\rho[\tilde{\gamma}^2, \Delta\widetilde{ahl}]$, which are necessary conditions for a hurricane risk premium our theoretical framework.

We find log consumption growth to be generally uncorrelated with log AHLG: $\rho[\Delta\tilde{c}, \Delta\widetilde{ahl}]$ does not significantly differ from zero in any of the two time periods. Only the most extreme natural disasters have loss potentials great enough to affect aggregate consumption growth and thus enter the marginal utility of a representative agent (Bauer et al., 2013; Braun et al., 2019b).[29] Such events, however, are clearly too rare to drive an empirical correlation on a decadal time scale. The correlation between AHLG and consumption inequality ($\rho[\tilde{\gamma}^2, \Delta\widetilde{ahl}]$), in contrast, is positive and significant for the time period 1995 to 2017. Further evidence in this regard is given by Figure 2, which depicts the 10-year rolling correlation between $\tilde{\gamma}^2$ and $\Delta\widetilde{ahl}$ together with the AMO Index time series from Figure 1. If individuals form their expectations for the next period based on historical data, this is a measure for $\rho_t[\tilde{\gamma}^2_{t+1}, \Delta\widetilde{ahl}_{t+1}]$. It is conspicuous that the latter turned positive and significant around the same time at which the most recent AMO warm phase began. We thus have a necessary condition for a hurricane risk premium from 1995 onwards. There are two plausible explanations for this development. One is the possibility that the enduring active period for Atlantic hurricanes discussed in the previous section gives rise to a larger number of scenarios in which high AHLG coincides with peaks in consumption inequality. The second one is a potential direct impact of hurricane activity

[29] As an example, consider a mega-thrust earthquake that directly hits a densely populated area of major economic importance such as the San Francisco bay area (Odell & Weidenmier, 2004).

on state-level consumption inequality. Apart from dealing property losses to households and businesses, natural disasters may depress economic activity (Botzen et al., 2019). Hurricanes in particular have been shown to impact production, wages, as well as employment, thus sharply reducing income and consumer spending in affected states (Auffret, 2003; Belasen & Polachek, 2008; Aladangady et al., 2017). In the next section, we will examine the sufficient condition for the risk premium, that is, asset (excess) returns which are negatively correlated with AHLG.

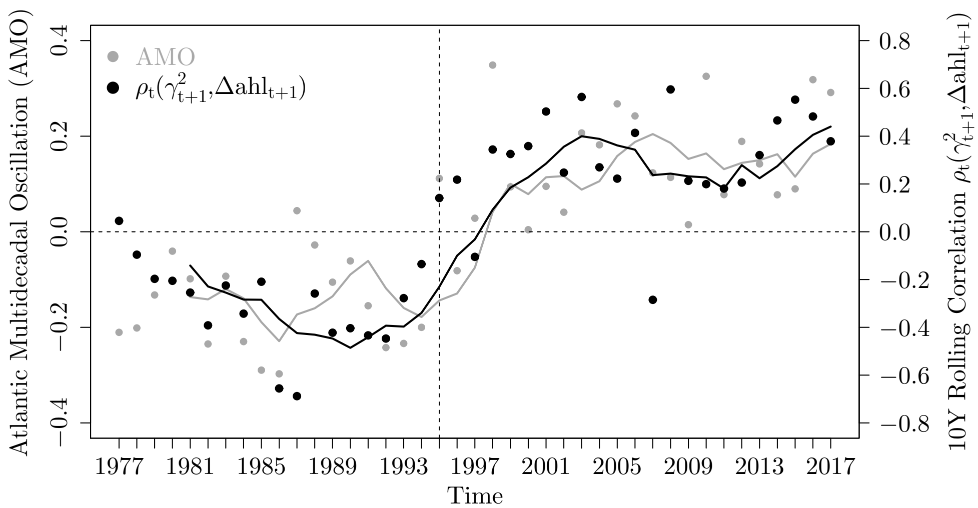

Figure 2: AMO and the Correlation Between Consumption Inequality and AHLG

This figure shows the annual time series of the Atlantic Multidecadal Oscillation (AMO) Index in °C (left axis) together with the 10-year rolling correlation between AHLG and consumption inequality ($\rho_t[\tilde{\gamma}^2_{t+1}, \Delta a\tilde{h}l_{t+1}]$) (right axis). Consumption inequality is measured by the state-level cross-sectional variance of personal income growth per capita (BEA data). The black and grey curves represent four-year moving averages of $\rho_t[\tilde{\gamma}^2_{t+1}, \Delta a\tilde{h}l_{t+1}]$ and the AMO Index, respectively.

5. Hurricane Risk Sensitivity and the Cross Section of Stock Returns

5.1. Stock Market Data

We consider all common stocks in the Center for Research in Security Prices (CRSP) trading data base (share code 10 and 11) on the NYSE, AMEX, and NASDAQ from January 1, 1963 through December 31, 2020. 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). Following Chabi-Yo et al. (2018), we exclude the stocks with the 1 percent lowest and the 5 percent highest market capitalisation in a given month t.[30] This leaves us with a total of 3,863,192 firm-month return observations. All returns are converted into excess returns using the 1-month T-Bill rate. In addition to the CRSP data, we download 25 Fama-French benchmark portfolios sorted by size and book-to-market equity from Ken French's website. Finally, we merge our excess return data with annual information on firm fundamentals from CRSP/Compustat Merged Fundamentals Annual database.

5.2. AHLG Mimicking Portfolio

Since AHLG is measured on an annual basis, we project it into the excess return space so as to obtain a mimicking portfolio that tracks the factor at a monthly frequency.[31] To this end, we proceed as follows. First, we run the following regression on the annual time series from 1963−2017:[32]

$$\Delta \widetilde{ahl}_t = \kappa_0 + \kappa_x' X_t + u_t, \tag{8}$$

where κ_0 and κ_x' are coefficients and X_t represents the excess returns on a set of base assets. For the latter, we select the 25 Fama-French benchmark portfolios. Subsequently, we normalize the estimated weights $\hat{\kappa}_x'$ so that they sum to one:

$$\hat{w}_x' = \frac{\hat{\kappa}_x'}{\mid \sum \hat{\kappa}_x' \mid}. \tag{9}$$

We can then construct the factor-mimicking portfolio $\mathrm{MP}_t^{\Delta \widetilde{ahl}}$ by applying the percentage weights $\hat{w}_x'$ to the excess return time series of the base assets X_t at a monthly frequency:

$$\mathrm{MP}_t^{\Delta \widetilde{ahl}} = \hat{w}_x' X_t. \tag{10}$$

[30] We will test the robustness of our main results against this selection in Section 6.

[31] This is common practice in related work (see, e.g., Adrian et al., 2014; Chen & Yang, 2019).

[32] Recall that, in contrast to our stock market data, the Weinkle et al. (2018) AHLG time series ends in 2017.

The upper part of Table 2 includes summary statistics for the factor $\Delta\widetilde{ahl}$ and the annual excess return time series of its mimicking portfolio $\mathrm{MP}_t^{\Delta\widetilde{ahl}}$. The correlation between $\Delta\widetilde{ahl}$ and $\mathrm{MP}_t^{\Delta\widetilde{ahl}}$ amounts to 0.76. This is more than twice as high as the values reported for other nontraded factors in recent work and thus implies a very good fit.[33]

	distribution					correlations	
1963-2017 (a.)	mean	median	s.d.	min.	max.	$\mathrm{MP}^{\Delta\widetilde{ahl}}$	p-val.
$\mathrm{MP}^{\Delta\widetilde{ahl}}$	0.051	0.157	0.766	−1.625	1.570	1.000	
$\Delta\widetilde{ahl}$	0.071	−0.049	3.312	−8.215	8.201	0.746	0.000***
1995-2017 (q.)	mean	median	s.d.	min.	max.	$\mathrm{MP}^{\Delta\widetilde{ahl}}$	p-val.
$\Delta\tilde{c}$	1.412	1.463	1.713	4.994	−3.671	−0.118	0.262
$\tilde{\gamma}^2$	0.561	0.183	1.401	9.807	0.063	0.178	0.089*

Table 2: Summary Statistics for AHLG and its Mimicking Portfolio

This table presents mean, median, standard deviation (s.d.), minimum and maximum for the time series of the factor AHLG ($\Delta\widetilde{ahl}$) and its mimicking portfolio ($\mathrm{MP}^{\Delta\widetilde{ahl}}$), formed with 25 Fama-French benchmark portfolios sorted by size and book-to-market equity. The upper part relates to annual time series data for the sample period 1963−2017. The lower part includes the results for quarterly time series data in the period 1995−2017. ***, ** and * indicate significance at the one, five, and ten percent levels.

5.3. Univariate Sorting

We now turn to the sufficient condition for a hurricane risk premium, that is, excess returns which are negatively correlated with AHLG. The following analyses take advantage of the plethora of stock market data from January 1963 to December 2020.[34] To begin with, in each month of the time series, we estimate a hurricane risk or AHLG beta ($\beta_i^{\Delta\widetilde{ahl}}$) for all stocks i in the respective cross section. This is done through the following time series regression with a rolling window, comprising the 60 months prior to the evaluation date:

$$R_{i,t}^e = \alpha_i + \beta_i^{\Delta\widetilde{ahl}}\ \mathrm{MP}_t^{\Delta\widetilde{ahl}} + u_{i,t}. \tag{11}$$

[33] See, e.g., Adrian et al. (2014) and Chen & Yang (2019)

[34] We extend the mimicking portfolio to 2020, using the weights estimated from the annual time series in the period 1963−2017.

Here $R_{i,t}$ and $\text{MP}_t^{\Delta\tilde{ahl}}$ are the monthly excess returns on the individual stocks and the mimicking portfolio, respectively. The 60-month rolling window ensures a sufficiently large number of observations for stable estimates and accounts for the time-varying character of hurricane risk. Taking into account that the correlation between an asset's excess return and the mimicking portfolio is a strong proxy for the correlation between its excess return and AHLG ($\rho[\tilde{R}^e_{t+1}, \text{MP}_t^{\Delta\tilde{ahl}}] \approx \rho[\tilde{R}^e_{t+1}, \Delta\tilde{ahl}]$), it is easy to see that the stocks' hurricane betas measure the sufficient condition for a hurricane risk premium:

$$\beta_i^{\Delta\tilde{ahl}} = \rho[\tilde{R}^e_{t+1}, \text{MP}_t^{\Delta\tilde{ahl}}] \frac{\sigma[\tilde{R}^e_{t+1}]}{\sigma[\text{MP}_t^{\Delta\tilde{ahl}}]}. \tag{12}$$

Economically, stocks of firms that suffer in the wake of hurricanes will exhibit excess returns with a negative $\beta^{\Delta\tilde{ahl}}$. On the other hand, stocks of firms that benefit from hurricanes will have excess returns with a positive $\beta^{\Delta\tilde{ahl}}$.[35] Based on our theory, we therefore expect to find a risk premium on the former relative to the latter. To examine this conjecture, we conduct univariate out-of-sample portfolio sorts. For each month t in the time series, we sort the cross section of stocks into five value-weighted quintile portfolios based on their $\beta^{\Delta\tilde{ahl}}$ over the previous 60 months.[36] If investors demand a hurricane risk premium, stocks with negative AHLG betas should earn higher excess returns in the next month than stocks with positive AHLG betas.

Table 3 shows the results for the portfolio sorts in the time periods January 1968 to December 1994 (Panel a) and January 1995 to December 2020 (Panel b). We report the portfolio with the highest negative (positive) hurricane risk betas as portfolio 1 (portfolio 5) at the top (bottom). The row labeled 1−5 contains the difference between the top and bottom quintiles. We will hereafter refer to this zero-investment portfolio as NMP (negative minus positive hurricane risk sensitivity). 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 (1992) three-factor model (FF3) and the Fama & French (1992) three-factor model extended by the Carhart (1997) momentum factor.

[35] An example is the construction industry, which has full order books when rebuilding begins post disaster.

[36] We provide the same results for equally-weighted portfolios in the Appendix.

Panel a) January 1968 to December 1994

	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	−2.644	0.439%	0.013%	0.036%	0.050%
2	−1.452	0.538%	0.153%	0.088%	0.139%
3	−0.749	0.505%	0.139%	0.018%	0.049%
4	−0.077	0.558%	0.204%	0.001%	0.023%
Portfolio 5	+0.980	0.441%	0.031%	−0.179%	−0.227%
NMP (1−5)	−3.624***	0.022%	−0.019%	0.216%	0.278%*
t-value	(−144.69)	(0.139)	(−0.112)	(1.299)	(1.652)

Panel b) January 1995 to December 2020

	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	−2.907	1.242%	0.316%	0.250%	0.328%
2	−1.367	0.985%	0.185%	0.077%	0.158%
3	−0.579	0.908%	0.213%	0.113%	0.171%
4	+0.138	0.837%	0.151%	0.089%	0.149%
Portfolio 5	+1.422	0.496%	−0.292%	−0.262%	−0.239%
NMP (1−5)	−4.329***	0.746%***	0.608%**	0.512%**	0.695%***
t-value	(−116.11)	(3.789)	(2.832)	(2.557)	(3.080)

Table 3: Univariate Out-of-Sample Portfolio Sorts (Value Weighted)

This table shows the results for the out-of-sample portfolio sorts in the time periods 1968−1994 (Panel a) and 1995−2020 (Panel b). All portfolios are formed on a value-weighted basis. The portfolio with the highest negative (positive) hurricane risk 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 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 (1992) three-factor model (FF3) and the Fama & French (1992) three-factor model plus the Carhart (1997) momentum factor. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ. 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 percent levels.

For both time periods, we observe considerable cross-sectional variation in the stocks' hurricane risk sensitivity. In Panel b), for example, the average AHLG betas range from −2.907 for portfolio 1 all the way up to +1.422 for portfolio 5. When considering column two, however, the two time periods differ distinctively. Despite the significant and large difference between the average betas of the quintile portfolios, Panel a) does not display a clear pattern in the average excess returns. This is consistent with our results in the previous section (see Table 1), according to which the necessary condition for a hurricane risk premium in the same time period was not fulfilled. In Panel b), on the other hand, the average excess returns exhibit a clean monotonic decrease from portfolio 1 to portfolio 5. Accordingly, the zero-investment portfolio NMP would have earned a highly significant average excess return of 0.746 percent per month, which is equivalent to 8.952 percent per year. Even after controlling for three common asset pricing models in columns three to five, we are left with a significant abnormal excess return of at least 0.512 percent or 6.144 percent p.a., an order of magnitude comparable to several existing anomalies.[37]

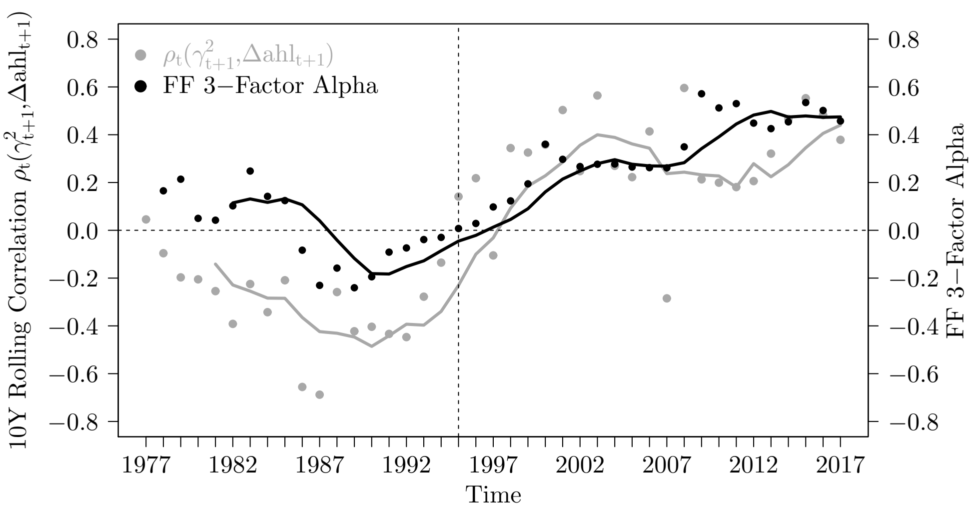

Figure 3: Time-Varying Fama-French 3-Factor Alpha of the Zero-Investment Portfolio NMP

This figure shows the annual time series of the 10-year rolling Fama & French (1992) three-factor (FF3) alpha for the zero-investment portfolio NMP on an equally-weighted basis (right axis). Annual values were calculated as the average of the monthly FF3 alphas in each year. The graph also shows the 10-year rolling correlation between AHLG and consumption inequality ($\rho_t[\tilde{\gamma}^2_{t+1}, \Delta a\tilde{h}l_{t+1}]$) (left axis) as a necessary condition for the hurricane risk premium. Consumption inequality is measured by the state-level cross-sectional variance of personal income growth per capita (BEA data). The black and grey curves represent four-year moving averages of the two series. The time period is determined by the length of the original sample (starting in 1963), the 60 months required for the rolling regressions that determine AHLG betas (shifts to 1968) and the ten year rolling window required for the FF3 time series regressions.

[37] Chabi-Yo et al. (2018), for example, find a stock market crash-sensitivity premium of 4.32 percent p.a. for the period from January 1963 to December 2012.

Figure 3 complements Table 8 with an illustration of the time-varying Fama & French (1992) three-factor (FF3) alpha for the zero-investment portfolio NMP on an equally-weighted basis. The alphas have been calculated in two steps. First, we performed a 10-year rolling regression with the FF3 model over the monthly NMP time series. Second, we converted the resulting monthly alphas into annual averages. This ensures comparability to the 10-year rolling correlation between AHLG and consumption inequality, which is also shown in the graph. The two solid curves represent four-year moving averages of both annual time series. The time period is determined by the length of the original time series (starting in 1963), the 60 months required for the rolling regressions that determine the hurricane risk betas (shifts us to 1968) and the ten year rolling window required for the FF3 time series regressions. We find that the hurricane risk premium follows a clear upward trend since the mid-1990s. This is consistent with the fact that both the necessary and sufficient conditions derived from our theoretical framework were fulfilled in the same time period.

5.4. Robustness of NMP Against Further Established Factors

Next, we regress the excess return time series of NMP on a comprehensive battery of major factors from the extant asset pricing literature. We present the results of these analyses in Table 4. Each model in columns one to seven combines MKT, SMB, HML from Fama & French (1992) plus MOM from Carhart (1997) with one additional factor. The extensions include the Chabi-Yo et al. (2018) lower tail dependence factor (LTD), the Sadka (2006) liquidity factor (SADKA), the Pástor & Stambaugh (2003) traded liquidity risk factor (PS), the Bali et al. (2011) lottery factor (LOT), the Baker & Wurgler (2006) sentiment index (SENT),[38] and the Frazzini & Pedersen (2014) betting-against-beta factor (BAB). Furthermore, in models eight through ten, we replace the Carhart (1997) momentum factor (MOM) with the Fama-French short-term plus long-term reversal factors (REVS, REVL), the investment and profitability factors of Fama & French (2015) (CMA, RMW) and the investment and profitability factors of Hou et al. (2014) (INV, ROE). In all ten cases, we are left with a statistically significant and economically large positive abnormal excess return of at least 0.505 percent per month (6.06 percent p.a.). As our zero-investment portfolio of stocks with negative minus positive hurricane loss sensitivity withstands a broad range of established factor model specifications, it seems to carry additional systematic risk information so far not explicitly carved out in the literature.

[38] SENT is orthogonalized with respect to a set of macroeconomic conditions

January 1995 to December 2020										
NMP	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1 MKT	0.087	0.216**	0.150*	0.054*	0.123*	0.083	0.089	0.199**	0.165***	0.139**
1 SMB	0.013	0.163**	0.152**	0.017	0.073	0.121	0.041	0.112	0.104**	0.050**
1 HML	0.233*	0.425**	0.488***	0.225*	0.354***	0.447***	0.205**	0.430***	0.136	0.187
1 MOM	−0.067	−0.108	−0.110	−0.072	−0.072	−0.109	−0.079			
2 LTD		−0.177								
3 SADKA			1.069							
4 PS				0.128**						
5 LOT					0.008					
6 SENT						0.129				
7 BAB							0.046			
8 REVS								−0.167*		
8 REVL								−0.114		
9 RMW									0.235	
9 CMA									0.118	
10 INV										0.171
10 ROE										0.047
alpha	0.695**	0.643**	0.532*	0.660***	0.579**	0.656**	0.662***	0.529**	0.505***	0.582**
t-value	(3.080)	(2.381)	(2.071)	(2.919)	(2.327)	(2.529)	(2.857)	(2.637)	(2.553)	(2.452)
R^2_{adj}	0.068	0.268	0.254	0.088	0.128	0.229	0.068	0.151	0.070	0.065
sample period	(1995-2020)	(1995-2012)	(1995-2012)	(1995-2020)	(1995-2020)	(1995-2010)	(1995-2020)	(1995-2020)	(1995-2020)	(1995-2020)

Table 4: Time Series Regressions of NMP (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 2020. 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 percent levels. Model (1) contains the market factor (MKT), consisting of all CRSP stocks, together with SMB and HML (Fama & French, 1992) as well as MOM (Carhart, 1997). The subsequent models (2) through (7) enrich model (1) with: the Chabi-Yo et al. (2018) lower tail dependence (LTD) factor, the Sadka (2006) liquidity factor (SADKA), the Pástor & Stambaugh (2003) liquidity risk factor (PS), the Bali et al. (2011) lottery factor (LOT), the Baker & Wurgler (2006) sentiment index (SENT), and the Frazzini & Pedersen (2014) betting-against-beta factor (BAB). In models (8) through (10), we we replace the Carhart (1997) momentum factor (MOM) with the Fama-French short-term plus long-term reversal factors (REVS, REVL), the investment and profitability factors of Fama & French (2015) (CMA, RMW) and the investment and profitability factors of Hou et al. (2014) (INV, ROE).

5.5. Robustness of NMP Against Alternative Measurements for AHLG

So far, the key variable in our empirical analyses has been AHLG computed from the Weinkle et al. (2018) hurricane loss data. Yet, if the hurricane risk premium is really driven by a fundamental economic mechanism, we should be able to confirm the results with other data sets for hurricane losses. We begin with the International Disasters Database (EM-DAT), which contains annual aggregate economic losses for various types of natural disasters in the United States. The database was launched by the Centre for Research on the Epidemiology of Disasters (CRED) in 1988. Economic losses in the EM-DAT database are available for the time period 1900 to 2017 and reported on a contemporaneous USD basis.[39] To rule out inflation effects, we adjust the data using the CPI index (base year 2009), provided by the Weinkle et al. (2018). We compute $\Delta \tilde{ahl}_t$ from the annual EM-DAT storm losses, reestimate the weights for the monthly mimicking portfolio on the $\Delta \tilde{ahl}_t$ time series from 1982 to 2017, and determine the hurricane betas ($\beta^{\Delta \tilde{ahl}}$) for each monthly cross section of stocks between 1995 and 2020.[40] Subsequently, we rerun our out-of-sample sorting analysis and form the zero-investment portfolio NMP.

The results of this robustness analysis for our main time period (1995−2020) and the stocks with significant AHLG betas can found in Panel a) of Table 5. Consistent with our previous findings, stocks with negative AHLG betas earned higher future excess returns than stocks with positive AHLG betas. The zero-investment portfolio NMP (1−5) exhibits a statistically significant and economically large average excess return of 0.796 percent per month (9.552 percent p.a.), which cannot be explained by the CAPM, the Fama & French (1992) three-factor model or its extension with the Carhart (1997) momentum factor.

As an additional measure for aggregate hurricane risk, we draw on the excess return time series of the Swiss Re U.S. Wind Catastrophe Bond Performance Index [Bloomberg ticker: SRUSWTRR]. Catastrophe bonds (cat bonds) are floating rate notes that securitize various types of NatCat risk.[41] Investors in U.S. wind cat bonds obtain a pure play exposure to the

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[39] For a small number of years (particularly early on), EM-DAT losses are unavailable. We fill these gaps with five-year rolling averages.

[40] We extend the time period for the construction of the mimicking portfolio from 1995−2017 to 1982−2017 to obtain a sufficient number of annual observations for a stable estimation of the 25 weights. As for the Weinkle et al. (2018) data, we extend the excess return time series of the mimicking portfolio to 2020. We exclude the stocks with the lowest 1 percent and 10 percent highest market capitalisation in a given month t.

[41] For a detailed explanation of cat bonds see, for example, Braun (2016).

insured losses caused by major hurricane events. Since insured losses and economic losses are highly correlated, the excess returns on the aforementioned Swiss Re performance index are an ideal measure for aggregate hurricane risk, which does not require the factor projection into the return space through a mimicking portfolio. Before calculating betas for each monthly cross section of stocks, we orthogonalize the excess returns of the cat bond index with respect to the market factor. Once more, we remove the stocks with the 5 percent highest and 1 percent lowest market cap. in each month and calculate betas for all monthly cross sections of stocks. As the cat bond index has been launched in 2002, we decide to use a 36-month instead of 60-month rolling window for the betas. In doing so, we are able to retain a longer time series for the analysis of NMP. Our evaluation time period therefore comprises the years from 2005 to 2020.

Panel b) of Table 5 contains the results for our robustness test with the cat bond index return time series. Two points are important to note. First, the betas now reflect a stock's sensitivity with regard to the excess returns on the cat bond index instead of AHLG. Second, the cat bond index exhibits an inverse relationship with AHLG. That is, if AHLG is high, cat bond excess returns will be low. This implies that, in contrast to Panel a), the portfolio with the largest negative (positive) average beta comprises the least (most) hurricane-risky stocks. Therefore, NMP in row number six is now calculated by subtracting the excess return time series of portfolio 5 from that of portfolio 1 (instead of vice versa). Consistent with our previous findings, stocks with positive cat bond index betas earned higher future excess returns than stocks with negative cat bond betas. The zero-investment portfolio NMP (5−1) again exhibits a statistically significant and economically large average excess return of 0.947 percent per month (11.364 percent p.a.), which cannot be explained by the CAPM, the Fama & French (1992) three-factor model or its extension with the Carhart (1997) momentum factor.

Panel a)	**EM-DAT Database, Storm Losses January 1995 to December 2020**				
	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	−0.146	1.318%	0.595	0.566	0.517
2	0.091	1.029%	0.234	0.202	0.299
3	0.235	0.721%	−0.202	−0.201	−0.020
4	0.363	0.738%	−0.400	−0.363	−0.146
Portfolio 5	0.602	0.522%	−0.817	−0.755	−0.624
NMP (1−5)	−0.749***	0.796%*	1.411%***	1.321%***	1.141***
	(−40.754)	(1.664)	(3.681)	(3.942)	(3.615)

Panel b)	**Swiss Re US Wind Cat Bond Index January 2005 to December 2020**				
	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	−2.594	0.405%	0.642	0.481	0.469
2	−0.909	0.684%	0.043	0.063	0.062
3	0.005	0.741%	0.067	0.057	0.047
4	0.947	0.877%	0.097	0.093	0.099
Portfolio 5	2.791	1.352%	0.353	0.199	0.240
NMP (5−1)	5.385***	0.947%***	1.003***	0.785***	−0.782***
	(−27.146)	(3.809)	(3.379)	(3.390)	(3.337)

Table 5: Univariate Out-of-Sample Portfolio Sorts (Value Weighted)

This table shows the results for the out-of-sample portfolio sorts. All portfolios are formed on a value-weighted basis. The row labeled NMP contains the zero-investment portfolio, capturing the hurricane risk premium. Panel a) presents the results for the EM-DAT storm loss data. The weights of the annual mimicking portfolio were estimated based on the data sample from 1982-2020. We focus on all firms with significant AHLG betas (73 percent of the overall sample). Panel b) shows the results based on the Swiss Re US Wind Cat Bond Performance Index, which does not require a mimicking portfolio. Since this index is only available from January 2002 on on monthly basis, we resort to a 36-month instead of 60-month rolling regression window for the estimation of the betas. This leads to the evaluation period from 2005 to 2020. Due to the fact that cat bonds exhibit negative returns when AHLG is high, NMP in Panel b) is calculated as portfolio 5 minus portfolio 1 instead of 1 minus 5 as in all previous analyses. Average betas are included in the first 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 (1992) three-factor model (FF3) and the Fama & French (1992) three-factor model plus the Carhart (1997) momentum factor. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ. 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 percent levels.

5.6. Multivariate Evidence

Below, we add multivariate evidence based on Fama & MacBeth (1973) regressions in the period from 1995 to 2020. 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 a set of firm-specific variables measured in t. The latter comprises each firm's AHLG beta, its size represented by the log market capitalization, its idiosyncratic excess return volatility, the coskewness of its excess return with the market's excess return, and the stock's market beta. We follow Ruenzi et al. (2013) and calculate the latter three measures based on a 6-year rolling window, leading up to month t. 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.

January 1995 to December 2020

	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$
$\beta^{\Delta\widetilde{ahl}}$	−0.071**	−0.071***	−0.068***	−0.056***	−0.033*
	(−2.505)	(−2.654)	(−3.129)	(−3.017)	(−1.828)
size		−0.073	−0.106***	−0.111***	−0.119***
		(−1.349)	(−2.581)	(−2.706)	(−2.628)
idiosyncratic vol.			−0.020**	−0.014	−0.023***
			(−1.173)	(−0.773)	(−1.749)
coskewness				−0.798***	−0.639***
				(−3.538)	(−3.287)
market beta					0.219
					(1.296)
alpha	0.971***	1.837**	2.545***	2.313***	2.375***
	(2.891)	(2.012)	(4.025)	(3.793)	(3.741)

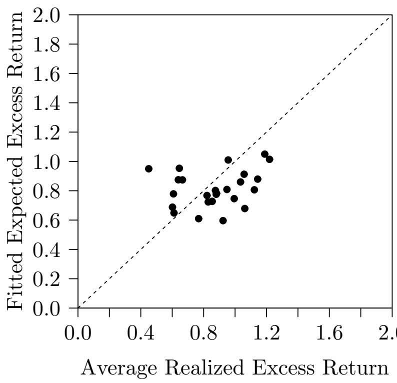
Table 6: Multivariate Fama & MacBeth (1973) Regression Results

This table presents the results of multivariate Fama & MacBeth (1973) regressions of excess returns in month t+1 on AHLG beta $\beta^{\Delta\widetilde{ahl}}$, size (log of market capitalization), idiosyncratic excess return volatility (idiosyncratic vol.), coskewness of the stock's excess returns with the market's excess returns (coskewness), and market beta in month t. The sample period is January 1995 to December 2020. In line with Ruenzi et al. (2013), idiosyncratic are calculated based on data until month t. The analysis covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ. The t-statistics in parentheses were computed using Newey & West (1987) standard errors with 4 monthly lags. ***, ** and * indicate significance at the one, five, and ten percent levels.

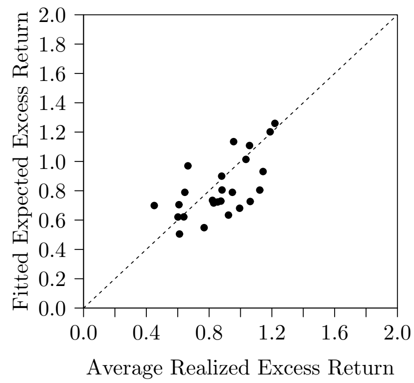
The first column shows the effect of the AHLG beta in isolation. As already found in our previous results, a stock's hurricane risk sensitivity has a statistically significant impact on the excess return in the next month. Stocks with a positive AHLG beta earn lower future excess returns than those with a negative AHLG beta. Economically, the former act as a hurricane risk insurance for stock portfolios. In contrast, the latter suffer when hurricane losses grow, causing investors to demand a hurricane risk premium. In columns two to five, we consecutively add the firm-specific controls size, idiosyncratic excess return volatility (idiosyncratic vola), coskewness, and market beta. Consistent with the existing asset pricing literature, all but one of these variables exhibit a statistically significant impact on the next-month returns. Nevertheless, the coefficient for the AHLG beta stays statistically significant negative throughout.

5.7. NMP and the Cross Section of Expected Excess Returns

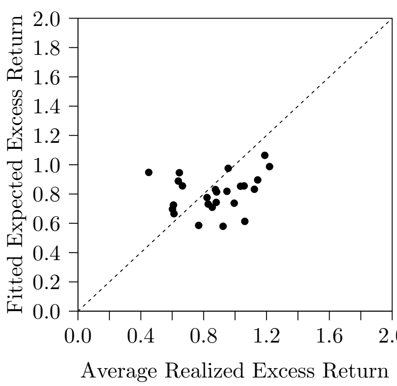
In this section, we show that adding NMP to the Fama & French (1992) three-factor model as well to its extension with the Carhart (1997) momentum factor, substantially reduces pricing errors in the cross section of 25 test portfolios sorted by size and hurricane risk sensitivity. In Figure 4, we have 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 2020. Test portfolios, for which the models' pricing errors are small, closely align along the 45-degree line. Evidently, NMP does improve the fit of both baseline specifications shown in subfigures (a) and (c). This graphical finding is underlined by a decrease in the root mean squared errors (RMSE) from 0.223 in (a) to 0.177 in (b) and from 0.237 in (c) to 0.185 in (d). Hence, NMP carries pricing information not included in the market factor, the high minus low (HML) book-to-market factor, the small minus big (SMB) size factor, and the momentum (MOM). In the next section, we probe NMP with an even larger set of established factors.



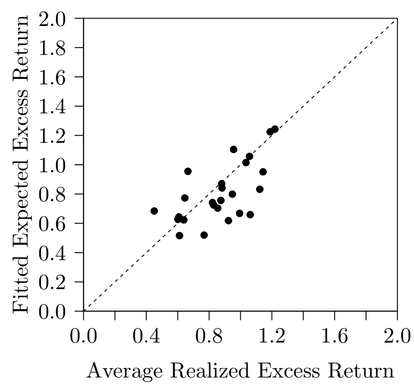
(a) FF Three-Factor Model



(b) FF Three-Factor Model + NMP



(c) FF Three-Factor Model + Momentum



(d) FF Three-Factor Model + Momentum + NMP

Figure 4: Model-Predicted versus Realized Mean Excess Returns

In this figure, the model-predicted expected excess returns (vertical axis) for 25 test portfolios sorted by size and hurricane beta are plotted against the corresponding average realized excess returns (horizontal axis). The sample period is January 1995 to December 2020. The smallest pricing errors can be found along the dashed 45-degree line.

6. Exploring the Economic Mechanism

6.1. Geographic versus Economic Hurricane Risk Exposure

Firms can suffer from direct or indirect impacts of natural disasters (Botzen et al., 2019). The former are mainly damages to physical property. The latter refer to all changes in economic activities caused by the disaster, such as supply chain interruptions, shortages of upstream inputs, and plunges in sales due to reduced consumer spending in disaster-struck areas. In many cases, production facilities, suppliers and customers are not geographically co-located with the firm's headquarters. Nevertheless, there are strong economic links (Cohen & Frazzini, 2008) and shocks from natural disasters have been shown to strongly propagate through production networks (Barrot & Sauvagnat, 2016).[42]. Hence, hurricanes can affect firms far away from their actual landfall location. This insight precludes a proper identification of the true hurricane risk exposure based on headquarters and production facilities from Compustat/CRSP in combination with hurricane landfall data.

To tackle this issue, we rely on textual analysis of public financial statements rather than the geographic location of establishments. Following Cohen et al. (2020), we download all complete 10-K, 10-K405 and 10-KSB filings from the SEC's EDGAR website, spanning the time period 2000−2017. We then match them with the CRSP stock market data. In doing so, we are able to project economic hurricane risk exposure into a geographic pattern. Specifically, we identify the headquarter location of all firms, which mentioned "hurricane loss" at least once in in their publicly available financial reports. Figure 5 illustrates the results in comparison to a NOAA map that shows the landfall states of all hurricanes between 1815 and 2012. As expected, the majority of the firms, which reported hurricane losses in their financial statements are headquartered in East Coast or Gulf Coast states. Those include Alabama (AL), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North Carolina (NC), New York (NY), South Carolina (SC), and Texas (TX). In addition, however, we also find firms reporting hurricane losses in states that are clearly disconnected from the actual physical events: Arizona (AZ), California (CA), Colorado (CO), Minnesota (MT), Oklahoma (OK), Oregon (OR), Utah (UT) and Washington (WA).

We exploit this finding to split our sample into two parts: states in which at least one headquartered firm was affected by a hurricane and states in which no firm disclosed hurricane

[42] In a current contribution, Buraschi & Tebaldi (2021) present a model for contagion in network economies firms and determine the asset pricing implications of the network topography.

losses. Subsequently, we then repeat the univariate sorting on both subsamples. We expect to see a risk premium for those firms, that are economically exposed to hurricane risk, be it through physical assets that are located inside the disaster area or through a deeper layer of economic linkages. Table 3 summarizes the results. The average excess return of the NMP portfolio (1-5) in the subsample of states with firms that reported hurricane losses amounts to a positive and significant 0.443 percent per month (5.316 percent p.a.). In contrast, the NMP portfolio formed from stocks in the remaining states without reports of hurricane losses turns out to be insignificant. This illustrates that economic rather than geographic exposure is the relevant basis for the hurricane risk premium.

Panel a) Headquarters with Hurricanes

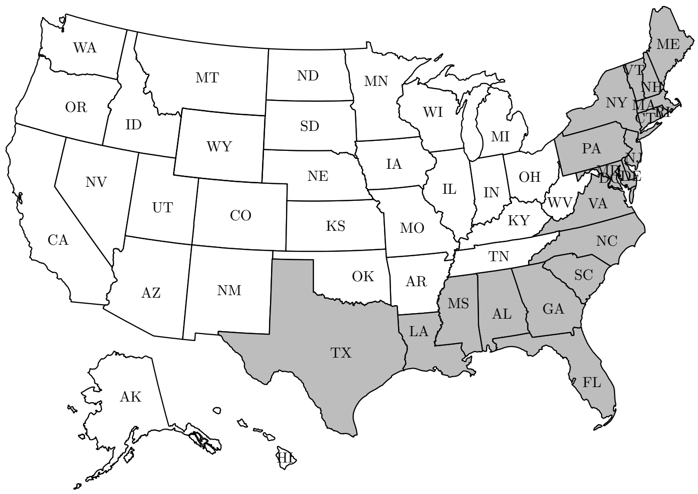
	Av. Beta	Av. Return
Portfolio 1	−3.116	1.367%
2	−1.455	1.084%
3	−0.611	0.917%
4	+0.164	0.787%
Portfolio 5	+1.524	0.489%
NMP (1−5)	−4.639***	0.878%**
t-value	(−126.29)	(4.203)

Panel b) Headquarters without Hurricanes

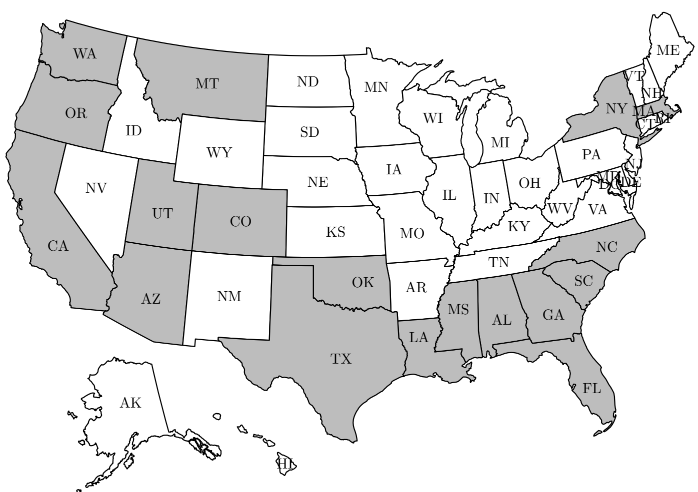
	Av. Beta	Av. Return
Portfolio 1	−2.311	0.955%
2	−0.959	1.004%
3	−0.317	0.835%
4	+0.319	0.792%
Portfolio 5	+1.537	0.693%
NMP (1−5)	−3.847***	0.261%
t-value	(−160.79)	(1.109)

Table 7: Spatial Out-of-Sample Portfolio Sorts (Value Weighted)

This table shows the results for the out-of-sample portfolio sorts in the time periods 1995−2020. All portfolios are formed on a value-weighted basis. The portfolio with the highest negative (positive) hurricane risk 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 sample in the upper panel covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ with headquarter location in the following states: AL, AZ, CA, CO, FL, GA, LA, MS, MT, NC, NY, OK, OR, SC, TX, UT, WA. The sample in the lower panel covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ with headquarter location in the remaining states. ***, ** and * indicate significance at the one, five, and ten percent levels.



(a) Historical Hurricane Landfalls (1815−2012)



(b) Economic Hurricane Exposure Map

Figure 5: Geographic vs. Economic Hurricane Exposure (2000−2017)

This figure shows actual hurricane landfalls between 1815 and 2012 (a) as reported by NOAA in comparison to states in which headquartered firms reported hurricane losses between 2000 and 2017 (b).

6.2. Hurricane Risk Over Time

In addition to the multidecadal dynamics driven by the AMO (see Figures 1 to 3), hurricane risk follows a clear intra-year pattern that can be exploited for identification. Specifically, hurricane risk is highest during the Atlantic hurricane season from June to November, peaking in the third quarter (see, e.g., Hallam et al., 2019). Outside the season, it is virtually zero. Figure 6 shows that the average excess returns of NMP in each quarter behave inversely to the corresponding hurricane arrival frequencies.[43] We seek to confirm this finding by way of a time series regression of the quarterly NMP excess returns on dummy variables for Q2, Q3 and Q4 (Q1 forms the base category), in which we control for differences in the annual market environment via year fixed effects (FE).[44] As the Breusch Pagan and Ljung-Box (lag of 3) tests turn out significant, all standard errors are heteroskedasticity and autocorrelation consistent (HAC). Panel a) of Table 8) shows a significant negative coefficient for the third quarter.

Next, we run a seasonal ARIMA model. Before we estimate the latter, we reduce the noise in the quarterly NMP series through a three-quarter rolling mean.[45] The smooth series is plotted in Figure 7 a). Next, we turn to the periodogram, ACF and PACF shown in Figure 7 b), c) and d) to identify an adequate model structure. The oscillating decline in the ACF is a sign for seasonality. The significant spikes at the first two lags of the ACF point to an MA(2) (second-order moving average), essentially picking up our filter. The PACF also shows a significant spike at lag one, indicative of an AR(1) (first-order autoregressive process). Further notable spikes occur at lags four and eight, reflecting a seasonal pattern recurring every four quarters. This is consistent with the large spike in the periodogram at a period of 3.6 (frequency 0.2778), which corresponds to the peak of the hurricane season in late August/early September. Given these observations, we fit an ARIMA(1,0,2)$(1,0,0)_4$ to the smooth quarterly NMP series and report the results in Panel b) of Table 8. The significant coefficient for the first-order seasonal autoregressive process SAR(1) at the fourth period provides further conclusive evidence for an annually repeating pattern. Hence, NMP adheres to the same intra-year seasonality as the underlying hurricane risk itself.

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[43] We use modeled instead of historical arrival frequencies, since those reflect the intra-year distribution of hurricane risk across time horizons that reach way beyond the historical records. The frequencies have been estimated by the catastrophe modeling firm AIR Worldwide and are published in Herrmann & Hibbeln (2021).

[44] In line with recent results by Hassani & Yeganegi (2020), we run the Ljung-Box with a lag of 3.

[45] This includes the current and previous two data points. The smooth quarterly series thus begins in Q3/1995.

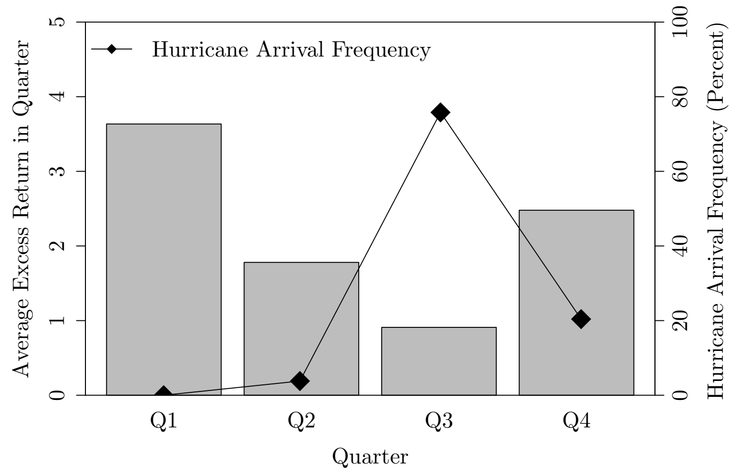


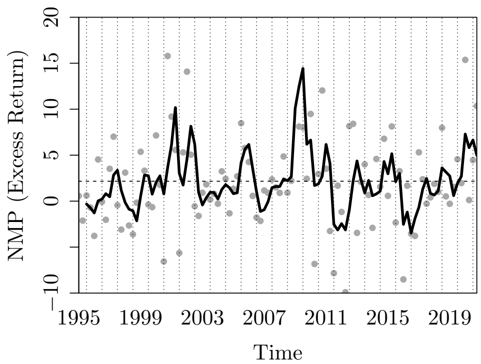
Figure 6: Quarterly Return Pattern of the Zero-Investment Portfolio NMP

This figure shows the average excess return per quarter of the zero-investment portfolio NMP on a value-weighted basis. The graph also shows the long-term hurricane arrival frequency in each quarter as estimated by the catastrophe risk modeling firm AIR. Due to the peak of the Atlantic hurricane season in August and September, Q3 is the most active period in terms of hurricane occurrence. This is mirrored by NMP, which tends to exhibit the lowest excess returns in Q3.

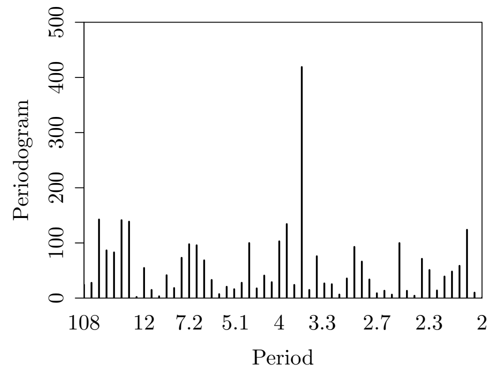
Panel a) TS Regression				**Panel b) SARIMA (smooth NMP)**			
	coeff.	p-val. (NW)	sig.		coeff.	p-val. (NW)	sig.
Intercept	1.0300	0.2784		AR(1)	0.2532	0.0105	**
Q2	−1.8547	0.1879		MA(1)	0.9350	0.0000	***
Q3	−2.7255	0.0321	**	MA(2)	1.0000	0.0000	***
Q4	−1.1560	0.3505		SAR(1)	0.3542	0.0004	***
df	75			df	98		
Year FE	Yes			AIC	4.1450		
BP	39.8430	0.0683	*	BIC	4.2737		
LB(3)	11.7330	0.0084	***	LB(3)	1.1184	0.7726	

Table 8: Time Series Analysis of the Zero-Investment Portfolio NMP

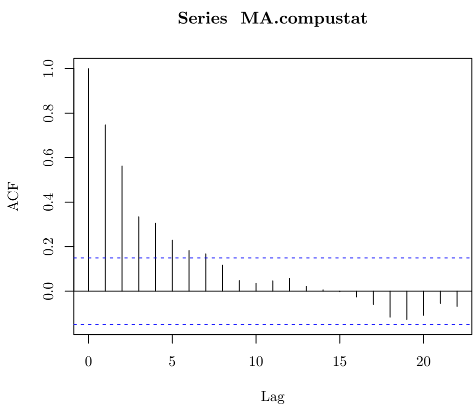
In Panel a), we report the coefficients (including intercept), p-values, significance levels and degrees of freedom (df) for a time series (TS) regression of the quarterly NMP series on dummy variables for the second, third and fourth quarter (first quarter forms the base category). We control for different annual regimes through year fixed effects (FE). In line with the significant Breusch-Pagan (BP) and Ljung-Box (LB) (lag of 3) tests, all standard errors are heteroskedasticity and autocorrelation consistent (HAC). Panel b) contains the coefficient estimates for an ARIMA(1,0,2)(1,0,0)$_4$ model fit to the smoothed (three-lag rolling mean) quarterly NMP series. The model structure has been identified via the ACF and PACF patterns in Figure 7 The significant first-order seasonal autoregressive component SAR(1) at the fourth period indicates an annually repeating pattern in the smoothed quarterly NMP series. ***, ** and * indicate significance at the one, five, and ten percent levels.



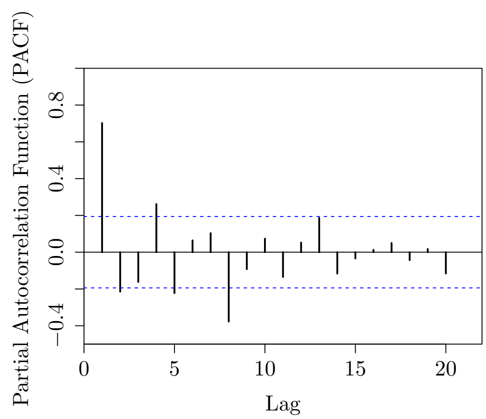
(a) NMP with Moving Average



(b) Periodogram



(c) ACF of NMP



(d) PACF of NMP

Figure 7: Time Series Patterns of the Zero-Investment Portfolio NMP

The four subfigures show: a) the quarterly excess returns of NMP over time (grey dots) together with the smoothed time series (rolling average of lag 3) and vertical dotted lines indicating the third quarters of each year, b) the periodogram of the smooth NMP time series, c) the autocorrelation function (ACF) of the smooth NMP time series and d) the partial autocorrelation function (PACF) of the smooth NMP time series. All indicators point to a seasonal pattern with a lag of about four quarters, reflecting the seasonality of the underlying natural peril.

6.3. Hurricane Risk Across Industries

Next, we explore the hurricane risk premium across industries. To this end, we split our sample of firms along SIC divisions and sort the stocks in each subsample based on hurricane risk beta. We find significant hurricane risk premiums for four out of ten industry divisions: construction (SIC codes 1500-1799), manufacturing (SIC codes 2000-3999), services (SIC codes 7000-8999), as well as finance, insurance and real estate (SIC codes 6000-6799). The respective results are summarized in Table 9.[46] To the best of our knowledge, there is no empirical research on the impact of natural disasters on firm profitability in different industries. We thus carefully interpret the results against known macroeconomic effects.

A significant hurricane risk premium for the financials division is highly plausible. Property-casualty insurers (p/c) are often particularly exposed to natural disaster risk (see Lamb, 1995) and recent work has documented that this impacts their costs of capital (see Ben Ammar et al., 2018).[47] There is also evidence of adverse effects on banks (see Schüwer et al., 2019) and Real Estate Investment Trusts (see Rehse et al., 2019).

Moreover, service-related industries contract when public life comes to a halt after the disaster (see Vigdor, 2008). A particularly vulnerable service sector in this regard is the tourism industry, which may also be hit by the destruction of key accommodation and transportation infrastructure. Manufacturing businesses on the other hand suffer from power outages and supply chain disruptions, even if they are geographically further away from but economically interconnected to the event (Barrot & Sauvagnat, 2016).

The last of the four divisions for which we document a significant hurricane risk premium is the construction sector. This result seems to be at odds with post-event demand-surge effects (see Döhrmann et al., 2017). However, there are several indications for reductions in the profitability of construction firms following major hurricanes. Hsiang (2010), for example, report a positive growth effect for the sector, but significantly higher labor costs. Similarly, Belasen & Polachek (2008) find average worker earnings to rise in hurricane struck counties.

[46] The results for the remaining industry divisions without significant effects are available from the authors upon request. Those are agriculture, forestry and fishing (SIC codes 0100-0999), mining (SIC codes 1000-1499), transportation, communications, electric, gas and sanitary services (SIC codes 4000-4999), wholesale trade (SIC codes 5000-5199), retail trade (SIC codes 5200-5999), and public administration (SIC codes 9100-9729).

[47] If we drill down to the industry instead of division level and exclusively consider p/c insurance stocks (SIC code 6331), the average excess return of the zero investment portfolio NMP increases to 0.70 percent per month (8.4 percent p.a.).

Vigdor (2008) reports an increase in the average weekly wage of New Orleans construction workers of almost 40 percent after Hurricane Katrina. Cui et al. (2015) highlight that the sector industry is affected by hurricanes through the disruption of construction projects and the decline in new building permits, which can lead to lasting losses for several years. Finally, in his analysis of direct and indirect effects of cyclones on different industries, Kunze (2021) documents beneficial demand effects, but no overall significant positive effect for the construction sector. He delivers a good summary of what might be at play: "One reason could be that the destruction of productive capital outweighs the higher number of orders".

Panel a)	**Manufacturing**			**Services**		
	Av. Beta	Av. Exc. Return	Carhart-Alpha	Av. Beta	Av. Exc. Return	Carhart-Alpha
Portfolio 1	−3.044	1.265	0.301	−3.311	1.215	0.295
2	−1.480	1.058	0.247	−1.517	1.131	0.264
3	−0.627	1.027	0.311	−0.626	1.005	0.233
4	0.149	0.820	0.090	0.230	0.943	0.175
Portfolio 5	1.521	0.726	−0.182	1.666	0.561	−0.324
NMP (1-5)	4.565	0.540	0.483**	4.977	0.654	0.619**
t-value	110.780	2.224	2.086	77.339	2.664	2.314

Panel b)	**Finance, Insurance and Real Estate**			**Construction**		
	Av. Beta	Av. Exc. Return	Carhart-Alpha	Av. Beta	Av. Exc. Return	Carhart-Alpha
Portfolio 1	−2.156	1.175	0.301	−3.096	1.975	0.715
2	−0.985	0.942	0.146	−1.754	1.471	0.433
3	−0.424	0.813	0.033	−0.937	1.297	0.295
4	0.093	0.892	0.148	−0.207	0.688	−0.174
Portfolio 5	0.971	0.663	−0.116	0.903	0.691	−0.109
NMP (1-5)	3.126	0.512	0.417*	3.999	1.284	0.825*
t-value	81.721	2.545	1.756	63.757	2.521	1.657

Table 9: Industry Analysis

This table shows the results for the out-of-sample portfolio sorts within industry sectors in the time periods 1995−2020. All portfolios are formed on a value-weighted basis. The portfolio with the highest negative (positive) hurricane risk 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.

6.4. Hurricane Risk Across Market Capitalizations

To test whether the hurricane risk premium depends on firm size, we conduct double-sorts. Each month, we first sort all stocks on the average market capitalisation over the prior 60 months. Subsequently, within each market capitalization quintile, we sort the stocks into five portfolios based on hurricane beta. Panel a) of Table 10 contains the average monthly excess returns of the double sorted portfolios (market capitalisation $\times$ hurricane beta) on a value-weighted basis without winsorization. In Panel b), we report the results that were obtained by excluding the 1 percent smallest and 5 percent largest firms according to average market cap.

Interestingly, the effect is generally absent for the 40 percent of firms with the lowest market capitalizations, potentially due to lesser interdependencies and network effects among small firms. The 60 percent of firms with the highest market capitalizations, in contrast, exhibit cross-sectional excess return differences based on hurricane risk.[48] Upon closer inspection, the effect seems to be largest for medium sized firms and then decreases again towards the last size quintile. This could be attributable to the fact that business diversification and general resilience is higher for large caps relative to mid caps. The winsorization applied in Panel b) is overall consistent with these observations. However, it shifts the peak of the hurricane risk premium by one notch to the right along the size dimension. The results for equally-weighted portfolios do not look materially different. They are available from the authors upon request.

[48] There is anecdotal evidence that even large tech giants are increasingly concerned about their natural disaster risk exposure. The Google holding company Alphabet, for example, has recently sought protection against earthquake losses through a catastrophe bond (see Artemis.bm).

Panel a) No Winsorization					
Market Cap.	Low	2	3	4	High
Portfolio 1	0.67	0.96	1.19	1.22	1.06
2	1.06	1.12	1.14	1.03	0.88
3	0.92	0.83	0.95	0.88	0.85
4	0.77	0.99	0.88	0.82	0.60
Portfolio 5	0.61	0.65	0.45	0.64	0.61
NMP (1−5)	0.06	0.31	0.74*	0.59**	0.45**
t-value	0.24	1.55	3.49	3.05	2.07

Panel b) Winsorization					
Market Cap.	Low	2	3	4	High
Portfolio 1	0.67	0.92	1.13	1.31	1.18
2	1.02	1.13	1.15	0.98	0.96
3	0.93	0.84	0.98	0.87	0.89
4	0.77	0.94	0.91	0.78	0.88
Portfolio 5	0.63	0.62	0.47	0.62	0.68
NMP (1−5)	0.04	0.30	0.66***	0.69***	0.50***
t-value	0.15	1.53	3.04	3.61	2.77

Table 10: Dependent Bivariate Portfolio Sorts (Size and Hurricane Beta), Value Weighted (1995−2020)

This table shows the results of bivariate portfolio sorts on size (first step) and hurricane beta (second step). Firm size is measured as the average market capitalization over the 60 months prior to the sorting date. Hurricane beta is estimated by means of a rolling regression over the 60 months prior to the sorting date. All portfolios are value weighted. Panel a) contains the results for the full sample of firms without winsorization. For the results reported in Panel b), we have excluded the firms with the 1 percent smallest and 5 percent largest average 60-month market caps in each month.

7. Conclusion

In this paper, we theoretically and empirically investigate the impact of hurricanes as a systematic risk factor on asset prices. Building on a consumption-based asset pricing model with heterogeneous agents following Constantinides & Duffie (1996), we identify a necessary and sufficient condition for a hurricane risk premium in the cross-section of stock returns. The necessary condition demands that aggregate hurricane loss growth (AHLG) is positively correlated with the variance of state-level income growth; the sufficient condition states that an asset's return is negatively related to AHLG. We examine both theoretical predictions for a hurricane premium in the cross-section of stock returns empirically. First, our results reveal that the correlation between AHLG and the variance of state-level income growth is significantly positive from 1995 to 2020, a period that is characterized by increased disaster losses from hurricane activity. Second, we find that stocks with a high sensitivity to hurricanes have higher future returns than stocks with a low sensitivity in this period. This hurricane premium is statistically significant at the 1% significance level and amounts to 8.9% per annum. The premium is not explained by traditional asset pricing risk factors nor firm characteristics, such as size, idiosyncratic volatility or coskewness. Turning to the economic mechanism behind the premium, we analyze firms' actual reports of hurricane losses in their financial statements. In line with intuition, we find that the hurricane premium is large and statistically significant only for those firms that were affected by a hurricane in the past, and, hence, show an increased likelihood for being hit by a hurricane in the future. We also document that excess returns on our hurricane risk factor follow the same seasonal pattern as the underlying hurricane risk itself. Furthermore, the hurricane risk premium exists for medium and large but not small firms and for industry divisions with plausible exposures to hurricane risk. This study provides a new perspective on the association between natural disasters and asset pricing. Acknowledging the positive relationship between firms' hurricane betas and future returns, we provide strong empirical evidence that firms – that are threatened by hurricane risk – exhibit higher cost of equity than their unexposed peers. How companies can react to this climate risk factor a is a potential interesting topic for future research.

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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 ($\mathrm{E}[X] = \mathrm{E}[Y] = \mathrm{E}[Z] = 0$) and unit variance ($\mathrm{E}[X^2] - \mathrm{E}[X]^2 = \mathrm{E}[Y^2] - \mathrm{E}[Y]^2 = \mathrm{E}[Z^2] - \mathrm{E}[Z]^2 = 1$). 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:

$$X = aY + X^*, \tag{13}$$

$$Z = bY + Z^*. \tag{14}$$

The expectation of X times Y is

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

and the expectation of Z times Y equals

$$\begin{aligned} \mathrm{E}[ZY] &= \mathrm{E}[(bY + Z^*)\,Y] \qquad (16) \\ &= b\mathrm{E}[Y^2] + \mathrm{E}[YZ^*]. \end{aligned}$$

$\mathrm{E}[YX^*]$ and $\mathrm{E}[YZ^*]$ are zero by design. Recall that X and Y have zero means and unit variances, implying that their standard deviations are $\sqrt{\mathrm{E}[X^2]} = 1$ and $\sqrt{\mathrm{E}[Y^2]} = 1$. Consequently, a and b represent the correlations between X and Y ($\rho[X,Y]$) as well as Z and Y ($\rho[Z,Y]$):

$$a = \mathrm{E}[XY] = \frac{\mathrm{E}[XY]}{\sqrt{\mathrm{E}[X^2]\cdot\mathrm{E}[Y^2]}} = \rho[X,Y], \tag{17}$$

$$b = \mathrm{E}[ZY] = \frac{\mathrm{E}[ZY]}{\sqrt{\mathrm{E}[Z^2]\cdot\mathrm{E}[Y^2]}} = \rho[Z,Y]. \tag{18}$$

Next, we derive the variances of X^* and Z^*. To this end, first rewrite the variances of X and Z, using (13) and (14):

$$\begin{aligned} \mathrm{E}[X^2] &= a^2\mathrm{E}[Y^2] + 2a\mathrm{E}[YX^*] + \mathrm{E}[X^{*2}] \\ &= a^2 + \mathrm{E}[X^{*2}] = 1, \end{aligned} \tag{19}$$

$$\begin{aligned} \mathrm{E}[Z^2] &= b^2\mathrm{E}[Y^2] + 2b\mathrm{E}[YZ^*] + \mathrm{E}[Z^{*2}] \\ &= b^2 + \mathrm{E}[Z^{*2}] = 1. \end{aligned} \tag{20}$$

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

$$\mathrm{E}[X^{*2}] = 1 - \rho[X, Y]^2, \tag{21}$$

$$\mathrm{E}[Z^{*2}] = 1 - \rho[Z, Y]^2. \tag{22}$$

Finally, inserting $a = \rho[X, Y]$ and $b = \rho[Z, Y]$ in (13) and (14) 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 $\rho[Z, Y]$:

$$\begin{aligned} \rho[X, Z] &= (\mathrm{E}[XZ] - \underbrace{\mathrm{E}[X] \cdot \mathrm{E}[Z]}_{=0}) / \underbrace{\sqrt{(\mathrm{E}[X^2] - \mathrm{E}[X]^2) \cdot (\mathrm{E}[Z^2] - \mathrm{E}[Z]^2)}}_{=1} \\ &= \rho[X, Y] \cdot \rho_t[Z, Y] \cdot \mathrm{E}[Y^2] + \rho[X, Y] \cdot \underbrace{\mathrm{E}[YZ^*]}_{=0} \\ &+ \rho[Z, Y] \cdot \underbrace{\mathrm{E}[YX^*]}_{=0} + \mathrm{E}[X^*Z^*] \\ &= \rho[X, Y] \cdot \rho[Z, Y] + \mathrm{E}[X^*Z^*]. \end{aligned} \tag{23}$$

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

$$\mathrm{E}[X^*Z^*] = \rho[X^*, Z^*]\sqrt{\mathrm{E}[X^{*2}] \cdot \mathrm{E}[Z^{*2}]} + \mathrm{E}[X^*] \cdot \mathrm{E}[Z^*]. \tag{24}$$

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

8.2. Sorting Results for Equally-Weighted Portfolios

Panel a): January 1968 to December 1994

	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	−3.055	0.632%	0.194%	−0.027%	0.045%
2	−1.463	0.675%	0.286%	0.039%	0.137%**
3	−0.727	0.713%	0.344%**	0.057%	0.105%*
4	−0.025	0.769%	0.244%**	0.072%**	0.133%**
Portfolio 5	+1.408	0.642%	0.02%	−0.141%**	−0.133%
NMP (1−5)	−4.464***	−0.009%	−0.054%	0.114%	0.178%
t-value	(−121.36)	(−0.406)	(0.269)	(0.943)	(1.295)

Panel b): January 1995 to December 2020

	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	−3.493	1.327%	0.305%	0.252%	0.487%*
2	−1.387	1.173%	0.372%*	0.263%**	0.411%***
3	−0.565	1.004%	0.308%*	0.202%**	0.316%***
4	+0.184	0.955%	0.262%	0.175%*	0.284%***
Portfolio 5	+1.889	0.799%	−0.101%	−0.127%	0.031%
NMP (1−5)	−5.382***	0.528%***	0.405%***	0.379%**	0.469%***
t-value	(−142.65)	(3.460)	(2.671)	(2.617)	(3.004)

Table 11: Univariate Out-of-Sample Portfolio Sorts (Equally-Weighted)

This table shows the results for the out-of-sample portfolio sorts in the time periods 1968−1994 (Panel a) and 1995−2020 (Panel b). All portfolios are formed on an equally-weighted basis. The portfolio with the highest negative (positive) hurricane risk 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 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 (1992) three-factor model (FF3) and the Fama & French (1992) three-factor model plus the Carhart (1997) momentum factor. The sample covers all U.S. common stocks traded on the NYSE/AMEX/NASDAQ. 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 percent levels, respectively.