

Hurricane Risk and Asset Prices

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Abstract

We examine hurricane exposure as a systematic risk factor in the U.S. stock market. Motivated by a consumption-based asset pricing model with heterogeneous agents, we derive two conditions for a hurricane risk premium in the cross-section of stock returns that can be tested empirically. We find that – in the last two decades – stocks that reacted negatively to aggregate hurricane losses outperformed stocks that reacted positively by more than 11% p.a. This hurricane risk premium can neither explained by standard asset pricing factors nor stock characteristics. Our results emphasize the relevance of climate risk for firms' cost of capital.

Keywords: Hurricane Risk, Consumption-Based Asset Pricing with Heterogeneous Agents, Empirical Asset Pricing, Climate Risk

JEL: C12, G01, G11, G12, G17

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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). 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.² 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). Hence, the last three decades not only set new records with regard to global temperatures (Sippel et al., 2020), but also in respect to extreme hurricane events³ and their economic impacts.⁴

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 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

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

²See Insurance Information Institute: Facts + Statistics: U.S. catastrophes.

³Sandy (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.

⁴Seven of the ten costliest disasters between 2010 and 2019 were hurricanes (see to Statista.com).

asset pricing. Specifically, we build on the model of Constantinides & Duffie (1996) with heterogeneous agents subject to idiosyncratic consumption shocks; in our case hurricanes represented by hurricane losses. 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 necessary conditions 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). 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 onwards, a time period of elevated hurricane activity. Since then individuals were thus confronted with large AHLG rates at times when consumption inequality and thus marginal utility was high.

We then examine the existence of a hurricane risk premium as well as its size and dynamics through a set of established asset pricing tests. For this purpose, we match all common U.S. stocks in the CRSP database between January 1963 and December 2020 with accounting figures from Compustat. To measure aggregate hurricane risk, we use AHLG computed from the Weinkle et al. (2018) data set. Following Adrian et al. (2014) and Chen & Yang (2019), we project the AHLG time series into the excess return space, constructing a factor mimick-

55 ing portfolio from the 25 size and book-to-market sorted Fama-French portfolios. The factor mimicking portfolio allows us to run the subsequent analyses at a monthly rather than annual frequency. For each stock, we estimate a beta with regard to the AHLG mimicking portfolio via 60-month rolling regressions. Stocks of firms that suffer (benefit) in the wake of hurricanes exhibit a negative (positive) AHLG beta.⁵ Based on the AHLG betas, we sort the stocks into
60 quintile portfolios and compute a zero investment portfolio of stocks with negative minus positive (NMP) AHLG beta. The NMP portfolio points to a hurricane risk premium of 0.746 percent per month (8.952 percent p.a.). Consistent with our theory and the empirically-documented correlation between AHLG and income inequality, this premium emerged in the last two and a half decades. The exact same time period is characterized by abnormally warm sea surface
65 temperatures in the North Atlantic and a scientifically-documented surge in hurricane activity (Goldenberg et al., 2001; Klotzbach & Gray, 2008).

We go on to 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 AHLG beta. We also consider
70 to which extent the time varying nature of hurricane risk is reflected in NMP. 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 this strong time series pattern for identification. First, we show graphically that the average quarterly excess returns
75 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
80 three diagnostics point to a seasonal first-order autoregressive 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.

⁵Depending on their business model, their exposure and a storm's landfall location, firms can both suffer or benefit from hurricanes. Construction firms, e.g., may experience a demand surge effect as the demand for skilled labour increases in the aftermath of severe natural disasters (see, e.g., Döhrmann et al., 2017).

Next, we take advantage of the catastrophe (cat) bond market to measure AHLG directly
85 in the excess return space. Cat bonds are traded financial instruments, whose excess returns
are driven by (insured) natural disaster risk. For each stock in our sample, we estimate a time-
varying beta with regard to the Swiss Re Cat Bond Performance Index by means of 36-month
rolling regressions, controlling for the Fama & French (1992) and Carhart (1997) factors. Since
a major part of the cat bond market covers U.S. hurricane risk, cat bond betas allow us to run
90 asset pricing tests without the need to create a factor mimicking portfolio for AHLG. The cat
bond betas need to be interpreted inversely to the AHLG betas. Stocks with positive cat bond
betas exhibit low returns when AHLG is high. They should therefore carry a risk premium
over stocks with negative cat bond betas. We isolate this risk premium by means of univariate
sorting, using (value and equally-weighted) quintile portfolios that rebalance every month.

105 We find that the average monthly excess return indeed monotonically increases from the
portfolio with the largest negative cat bond beta to the portfolio with the largest positive cat
bond beta. The effect is highly significant and large: between 2006 and 2020, a zero-investment
portfolio of stocks with positive minus negative (PMN) cat bond betas, earned an average excess
return of 0.97 percent per month (11.64 percent p.a.), with a t-statistic of 3.44. The largest
100 part of this spread (0.69 percent per month) 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.

We continue with multivariate analyses. Value-weighted Fama & MacBeth (1973) regressions
show that the effect of the cat bond betas stays statistically and economically strong when we
105 control for firm-specific characteristics, such as market beta, size, idiosyncratic volatility and
coskewness. Subsequently, we run a series of time series regressions of PMN on a broad battery
of established factors.⁶ All of them leave us with large significant positive alphas of at least 0.64
percent per month (7.68 percent p.a.).

In the next step, we inspect the relation of the risk premium and the economic hurricane expo-
110 sure of firms. As firms can exhibit close economic links (Cohen & Frazzini, 2008) and shocks from

⁶Those 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) liq-
uidity 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 fac-
tors, the Fama & French (2015) operating profitability and investment factors, as well as the investment and
profitability factors Hou et al. (2014)

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
115 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 their financial statements. We identify their states of incorporation and split the sample into two parts: states in which at least one headquartered
120 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 those states that are economically (not just geographically) exposed to hurricane risk. The second, unexposed subsample, in contrast, shows no significant effect.

125 Finally, we examine the hurricane risk premium by economic sector. To this end, we split our sample into primary, secondary and tertiary sector firms. We find significant hurricane risk premiums for the latter two. This is consistent with earlier results in the literature, documenting that hurricane risk may affect manufacturing and services firms via direct exposures, supply chain disruptions, revenue drops, order book effects, and labor market reactions. We
130 provide a number of extracts from 10-K reports to illustrate how secondary sector firms in the manufacturing and construction business suffered or benefited from the occurrence of historical hurricanes. Similarly, we provide such examples for tertiary sector firms from two industries: accommodation and food services and financials.

Our results have several important implications. First, we unveil a novel transmission chan-
135 nel 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
140 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 concentra-
145 tion 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.⁷

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
150 consumption shocks. In Section 4, we then discuss the systematic properties of hurricane risk,
estimate AHLG and test its empirical correlations with macroeconomic fundamentals. Section 5
contains all asset pricing tests. We begin with the description of our stock market data before
moving on to the results of the univariate sorting on AHLG betas. Moreover, we analyze the
impact of NMP in the cross section of expected excess returns and we explore its time series
155 pattern. We continue with univariate sorting and Fama & MacBeth (1973) regressions based
on cat bond betas as well as time series regressions of PMN on a broad range of established
factors. Lastly, we explore how the hurricane risk premium relates to economic versus geographic
hurricane exposure and to economic sectors. In Section 6, we then summarize our findings and
draw our conclusion.

160 **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
165 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).⁸ 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
170 Hong et al. (2019) and Lanfear et al. (2019). The former search for a drought risk premium in

⁷See NOAA Global Warming and Hurricanes: An Overview of Current Research Results for an extrapolation of hurricane risk in the 21st century.

⁸A 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).

the stock returns of food companies, whereas the latter provide evidence that the well-known 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.⁹ Ex-
tant studies in this field have considered the impact on growth (Strobl, 2011; Cavallo et al., 2013;
175 Felbermayr & Gröschl, 2014), consumption (Sawada & Shimizutani, 2008; Aladangady et al.,
2017), income (Miljkovic & Miljkovic, 2014), firm sales (Addoum et al., 2020), and local la-
bor 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 implica-
tions of natural catastrophe (NatCat) risk for policymakers (Michel-Kerjan & Kunreuther,
180 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 regula-
185 tory 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 find-
ings are linked to recent work on the importance of climate risks for institutional investors
190 (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
195 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 con-
sider implied event probabilities for valuation and the prediction of seasonality (Beer & Braun,
200 2021; Herrmann & Hibbeln, 2021).

Finally, our results enrich a particular stream of the general asset pricing literature, which

⁹For a comprehensive overview of this literature, refer to Kousky (2014) and Botzen et al. (2019).

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, 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.¹⁰ 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 largely unavailable or unaffordable. Accordingly, empirical evidence rejects the consumption insurance hypothesis in this context (Sawada & Shimizutani, 2007). The reluctance of insurance companies to provide widespread coverage has, among others, been explained by high capital requirements, market imperfections,

¹⁰For 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).

and nondiversification traps (Jaffee & Russell, 1997; Froot, 2001; Ibragimov et al., 2009).¹¹

230 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 direct flood losses.¹² In addition, flooding events inflict serious business interruption losses on the economy (Vilier et al., 2014).

235 We begin our theoretical considerations with the model of Constantinides & Duffie (1996). Assume that consumers exhibit homogeneous preferences, but heterogeneous consumption (income) processes that are nonstationary and heteroskedastic.¹³ 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:

$$E_t[\tilde{R}_{t+1}^e] = -\frac{\text{cov}_t[\tilde{H}_{t+1}, \tilde{R}_{t+1}^e]}{E_t[\tilde{H}_{t+1}]}, \quad (1)$$

where \tilde{R}_{t+1}^e 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:

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

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Here, α equals the RRA coefficient¹⁴, β is the subjective time-discount factor, and $\tilde{\gamma}_{t+1}^2$ is the (cross-sectional) variance of individual consumption growth. Abusing terminology, we will refer to $\tilde{\gamma}_{t+1}^2$ as consumption 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, 245 $\tilde{\gamma}_{t+1}^2 = 0$ so that (1) reduces to the Euler equation of the standard representative-investor consumption-based model.

¹¹Attempts 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).

¹²See Munich Re (2020): The flood insurance gap in the United States.

¹³In 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.

¹⁴Since $u(C_t) = \frac{C_t^{1-\alpha}}{1-\alpha}$, $\alpha \rightarrow 1$ leads to $u(C_t) = \ln(C_t)$. The marginal utility is therefore $u'(C_t) = C_t^{-\alpha}$

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 :

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

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

$$cov_t[\tilde{H}_{t+1}, \tilde{R}_{t+1}^e] = E_t[\tilde{H}_{t+1}] \cdot cov_t[\tilde{h}_{t+1}, \tilde{R}_{t+1}^e], \quad (3)$$

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:

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

which implies

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

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

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

In addition to the variables of the classical representative investor model included in the first summand of (6), we have a second driver of the risk premium, governed by the correlation 260 $\rho_t[\tilde{\gamma}_{t+1}^2, \tilde{R}_{t+1}^e]$ as well as the standard deviations $\sigma_t[\tilde{\gamma}_{t+1}^2]$ and $\sigma_t[\tilde{R}_{t+1}^e]$. 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 265 $\Delta\tilde{a}hl_{t+1} = \ln(\tilde{A}HL_{t+1}/\tilde{A}HL_t)$ be log AHLG, with $\tilde{A}HL_t$ denoting aggregate hurricane losses at

time t . We proceed by demeaning and standardizing the key random variables $\Delta\tilde{c}_{t+1}$, $\tilde{\gamma}_{t+1}^2$, and $\Delta\tilde{a}\tilde{h}l_{t+1}$. This allows us to decompose the correlations in (6) as follows:¹⁵

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

\tilde{c}_{t+1}^* , \tilde{R}_{t+1}^{e*} as well as $\Delta\tilde{\gamma}_{t+1}^{*2}$ reflect those components of the random variables \tilde{c}_{t+1} , \tilde{R}_{t+1}^e and $\tilde{\gamma}_{t+1}^2$ that are orthogonal to $\Delta\tilde{a}\tilde{h}l_{t+1}$.¹⁶ Equation (7) predicts a hurricane risk premium based on expected correlations between macroeconomic fundamentals and AHLG ($\rho_t[\Delta\tilde{c}_{t+1}, \tilde{a}\tilde{h}l_{t+1}]$, $\rho_t[\tilde{\gamma}_{t+1}^2, \Delta\tilde{a}\tilde{h}l_{t+1}]$) and the expected correlation between the excess return on a risky asset and AHLG ($\rho_t[\tilde{R}_{t+1}^e, \Delta\tilde{a}\tilde{h}l_{t+1}]$). By the law of iterated expectations, this equation also holds for unconditional moments.

Given our theoretical framework, we can now aim for an empirical verification in two steps. 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.

¹⁵The mathematical derivation underlying the decomposition of $\rho_t[\Delta\tilde{c}_{t+1}, \tilde{R}_{t+1}^e]$ and $\rho_t[\tilde{\gamma}_{t+1}^2, \tilde{R}_{t+1}^e]$ can be found in the Appendix (Section 7). Specifically, we apply Equation (21) with $X = \Delta\tilde{c}_{t+1}$ or $X = \tilde{\gamma}_{t+1}^2$ as well as $Y = \Delta\tilde{a}\tilde{h}l_{t+1}$ and $Z = \tilde{R}_{t+1}^e$.

¹⁶Note that (7) does no longer contain standard deviations, because the variables have been standardized.

4. Hurricane Risk and Macroeconomic Fundamentals

4.1. Hurricane Risk Properties

280 Hurricane risk is severe¹⁷ 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.¹⁸ Taking into account the ever-growing integration of economies through firm-linkages and production
285 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
290 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 SST on interannual and decadal time scales (Kossin & Vimont, 2007; Smith et al., 2010; Hallam et al., 2019).¹⁹ Research indicates that, after a time of subdued hurri-
295 cane 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).²⁰ Extreme hurricanes are more frequent in active periods compared to quiet periods (Donnelly & Woodruff, 2007). Intensity is
300 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).

¹⁷Hurricanes account for the by far largest fraction of natural disaster losses in the U.S. (Swiss Re, 2019).

¹⁸See Insurance Information Institute: Hurricane Katrina: The Five Year Anniversary.

¹⁹The climate phenomena behind these variations are the El Niño Southern Oscillation and the Atlantic Multidecadal Oscillation.

²⁰Both duration and intensity are major drivers of a cyclone's destructiveness (Emanuel, 2005).

4.2. Hurricane Risk Measurement

305 To measure hurricane losses, 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. The main data includes the year and state of occurrence for each event, its rank on the Saffir-Simpson scale,²¹ 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) 310 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 315 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 320 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).²² Moreover, the geographic region in which cyclones can form has expanded and the storms themselves are able to travel greater distances away from the tropics, reaching previously unharmed locations (Lucas et al., 2014; Kossin et al., 325 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 than 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).

²¹Hurricanes 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.

²²Both ACE and PDI are aggregates of intensity, frequency, and duration and therefore represent a concise metrics of hurricane activity over a whole season.

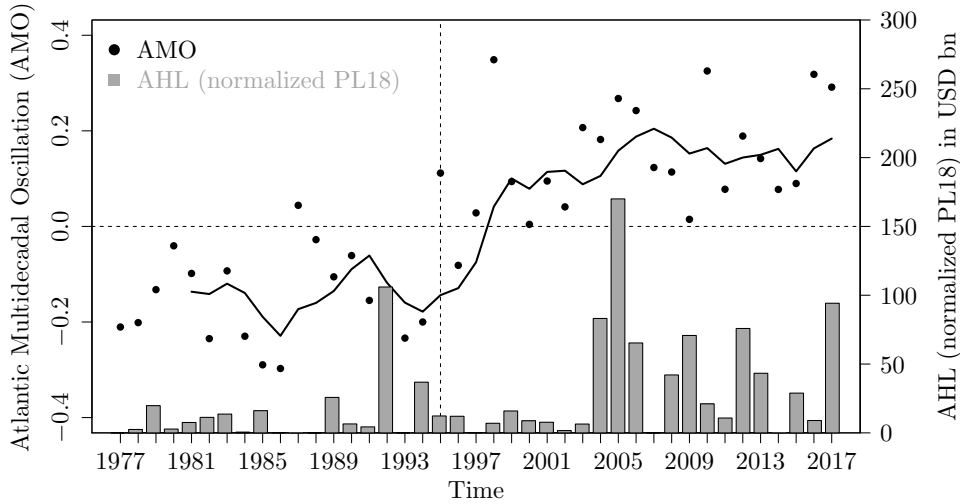


Figure 1: AMO and Aggregate Hurricane Losses (AHL)

This figure shows the Atlantic Multidecadal Oscillation (AMO) Index in $^{\circ}\text{C}$ (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.

330 *4.3. Correlations of AHLG 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.²³ $\Delta\tilde{ahl}$ is calculated based on the non-normalized 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).²⁴ Finally, we estimate $\tilde{\gamma}^2$ by means of the state-level variance of income growth, using annual personal income statistics (per capita) from the BEA.²⁵ 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.

²³We adjust nominal figures using the Consumer Price Index (CPI) (base year 2012).

²⁴Kroencke (2017) argues that the National Income and Product Accounts (NIPA) consumption data are subject to measurement errors generated by time aggregation and filters.

²⁵State-level consumption data is unavailable. Hence, measuring consumption inequality through income inequality is a common procedure in the asset pricing literature (see, e.g., Chen & Yang, 2019) and beyond (see, e.g., Attanasio & Pistaferri, 2016).

	distribution					correlations	
	mean	median	s.d.	min.	max.	$\Delta\tilde{a}\tilde{h}l$	p-val.
1978–1994							
$\Delta\tilde{a}\tilde{h}l$	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							
$\Delta\tilde{a}\tilde{h}l$	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 ($\Delta\tilde{a}\tilde{h}l$), log consumption growth ($\Delta\tilde{c}$), and consumption inequality ($\tilde{\gamma}^2$). Moreover, it includes empirical estimates for the correlations $\rho[\Delta\tilde{c}, \Delta\tilde{a}\tilde{h}l]$ and $\rho[\tilde{\gamma}^2, \Delta\tilde{a}\tilde{h}l]$.

340 We find log consumption growth to be generally uncorrelated with log AHLG: $\rho[\Delta\tilde{c}, \Delta\tilde{a}\tilde{h}l]$ 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).²⁶ Such events, however, are clearly too rare to drive an empirical correlation on a
345 decadal time scale. The correlation between AHLG and consumption inequality ($\rho[\tilde{\gamma}^2, \Delta\tilde{a}\tilde{h}l]$), 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 $\Delta\tilde{a}\tilde{h}l$ 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 $\rho_t[\tilde{\gamma}_{t+1}^2, \Delta\tilde{a}\tilde{h}l_{t+1}]$. It is
350 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. First, the enduring active period for Atlantic hurricanes discussed in the previous section may give rise to a larger number of scenarios in which high AHLG coincides with peaks in consumption
355 inequality. Second, there may be a direct impact of hurricane activity on state-level consumption

²⁶As 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).

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).
 360 In the following, we will examine the second condition for the hurricane risk premium, i.e., a negative correlation between the excess returns of an asset and AHLG.

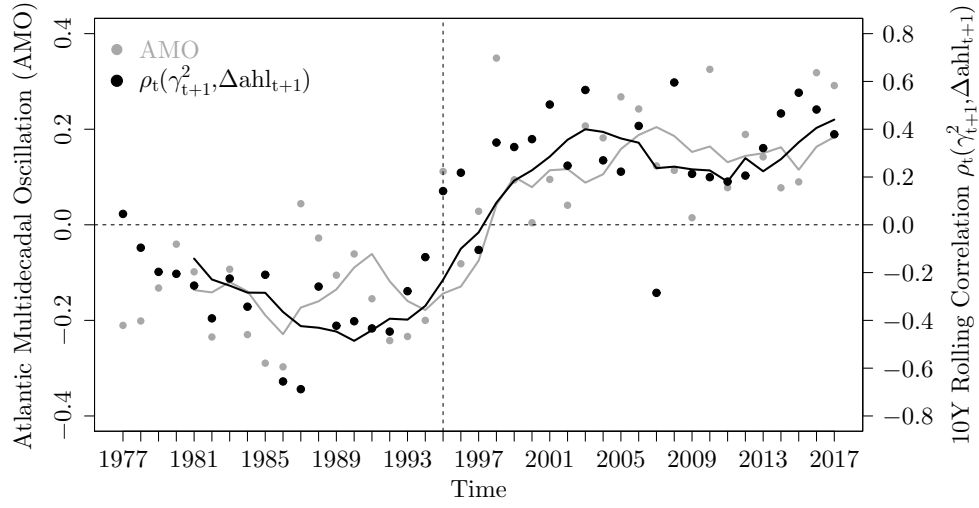


Figure 2: AMO and the Correlation Between Consumption Inequality and AHLG

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

5. Hurricane Risk and the Cross Section of Stock Returns

5.1. Stock Market Data

We consider all common stocks in the CRSP data base (share code 10 and 11) traded on the NYSE, AMEX, and NASDAQ from January 1, 1963 to December 31, 2020. We adjust the raw CRSP holding-period returns for delisting events, following Shumway (1997). To be able to run Fama & MacBeth (1973) regressions and identify the headquarter locations of the firms, we match the CRSP sample to the CRSP/Compustat Merged (CCM) data from the Wharton Return Data Service (WRDS). Moreover, to add the firms' book equity variable to the CRSP data and compute the book-to-market (BM) ratio, we follow the procedure of Fama & French (1992), assuming that the calendar year data is not known until the end of June of the next year. Applying these filters leaves us with a total of 632,588 firm-month return observations. All returns are converted into excess returns using the one-month T-Bill rate.

5.2. AHLG Mimicking Portfolio

We use the AHLG time series computed from the non-normalized Weinkle et al. (2018) loss data (see fourth section) as a measure for hurricane risk. Since this time series is only available on an annual basis, we project it into the excess return space to obtain a mimicking portfolio that tracks the factor at a monthly frequency. To this end, we proceed as follows. First, we run the following regression on the annual time series from 1963–2017:²⁷

$$\Delta \tilde{a}hl_t = \kappa_0 + \kappa'_x X_t + u_t, \quad (8)$$

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

$$\hat{w}'_x = \frac{\hat{\kappa}'_x}{|\sum \hat{\kappa}'_x|}. \quad (9)$$

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

$$MP_t^{\Delta \tilde{a}hl} = \hat{w}'_x X_t. \quad (10)$$

²⁷Recall 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 $\Delta\tilde{a}\tilde{h}l$ and the annual excess return time series of its mimicking portfolio $MP_t^{\Delta\tilde{a}\tilde{h}l}$. The correlation between $\Delta\tilde{a}\tilde{h}l$ and $MP_t^{\Delta\tilde{a}\tilde{h}l}$ 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.²⁸

	distribution					correlations	
	mean	median	s.d.	min.	max.	$MP^{\Delta\tilde{a}\tilde{h}l}$	p-val.
1963-2017 (a.)							
$MP^{\Delta\tilde{a}\tilde{h}l}$	0.051	0.157	0.766	-1.625	1.570	1.000	
$\Delta\tilde{a}\tilde{h}l$	0.071	-0.049	3.312	-8.215	8.201	0.746	0.000***
1995-2017 (q.)							
$\Delta\tilde{c}$	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 ($\Delta\tilde{a}\tilde{h}l$) and its mimicking portfolio ($MP^{\Delta\tilde{a}\tilde{h}l}$), 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 correlations of $MP^{\Delta\tilde{a}\tilde{h}l}$ with macroeconomic fundamentals for quarterly time series data in the period 1995–2017. ***, ** and * indicate significance at the one, five, and ten percent levels.

5.3. AHLG Betas and Univariate Sorting

Next we compute the stocks' monthly AHLG betas, denoted $\beta_i^{\Delta\tilde{a}\tilde{h}l}$, which reflect the sensitivity of their excess returns with regard to $MP_t^{\Delta\tilde{a}\tilde{h}l}$.²⁹ Stocks of firms that suffer (benefit) in the wake of hurricanes will exhibit a negative (positive) $\beta_i^{\Delta\tilde{a}\tilde{h}l}$.³⁰ Since $\beta_i^{\Delta\tilde{a}\tilde{h}l} = \rho[\tilde{R}_{t+1}^e, MP_{t+1}^{\Delta\tilde{a}\tilde{h}l}] \frac{\sigma[\tilde{R}_{t+1}^e]}{\sigma[MP_{t+1}^{\Delta\tilde{a}\tilde{h}l}]}$ and $\rho[\tilde{R}_{t+1}^e, MP_{t+1}^{\Delta\tilde{a}\tilde{h}l}] \approx \rho[\tilde{R}_{t+1}^e, \Delta\tilde{a}\tilde{h}l_{t+1}]$, the AHLG betas can be used to test our second condition for a hurricane risk premium. To estimate them for any given month, we regress the stock's excess returns in the previous 60 months on the excess returns of the mimicking portfolio.

We search for the risk premium by means of univariate out-of-sample portfolio sorts, i.e., we

²⁸See, e.g., Adrian et al. (2014) and Chen & Yang (2019).

²⁹We extend the mimicking portfolio to 2020, using the weights estimated for the period 1963–2017.

³⁰Hurricane losses may, e.g., benefit the construction industry through post-disaster rebuilding mandates.

sort the monthly cross sections of stocks into value-weighted quintile portfolios based on their AHLG betas. Following Chabi-Yo et al. (2018), we exclude the stocks with the one percent
390 lowest and the five percent highest market capitalisations in a given month. The portfolio with the largest negative (positive) average AHLG beta comprises the most (least) hurricane-risky stocks. Thus, 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 value-weighted portfolio sorts in the time periods January
395 1968 to December 1994 (Panel a) and January 1995 to December 2020 (Panel b).³¹ We report the portfolio with the highest negative (positive) AHLG betas as portfolio 1 (portfolio 5) at the top (bottom). The row labeled 1–5 contains the corresponding zero-investment portfolio, which will hereafter refer to as NMP (negative minus positive AHLG beta). Average betas are included in the first column and average excess returns in the second column. The remaining
400 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 Carhart (1997) momentum factor.

For both time periods, we observe considerable cross-sectional variation in the stocks' hurri-
405 cane risk sensitivity. In Panel b), e.g., 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 fourth section, according to which the first
410 condition for a hurricane risk premium in the same time period was not fulfilled (see Table 1). 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 the common asset pricing models in columns
415 three to five, we are left with a significant abnormal excess return of at least 0.512 percent or 6.144 percent p.a.. This is on an order of magnitude comparable to several existing factors. Chabi-Yo et al. (2018), e.g., find a stock market crash-sensitivity premium of 4.32 percent p.a. for the period from January 1963 to December 2012.

³¹The results for equally-weighted portfolios can be found 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 for AHLG Betas (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. We exclude the stocks with the one percent lowest and the five percent highest market capitalisations in a given month. 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 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.

5.4. NMP and the Cross Section of Expected Excess Returns

420 Adding NMP to the Fama & French (1992) three-factor model and to its extension with the
 Carhart (1997) momentum factor reduces pricing errors in the cross section of 25 test portfolios
 sorted by size and AHLG beta. In Figure 3, 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
 425 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 HML, SMB, and MOM.

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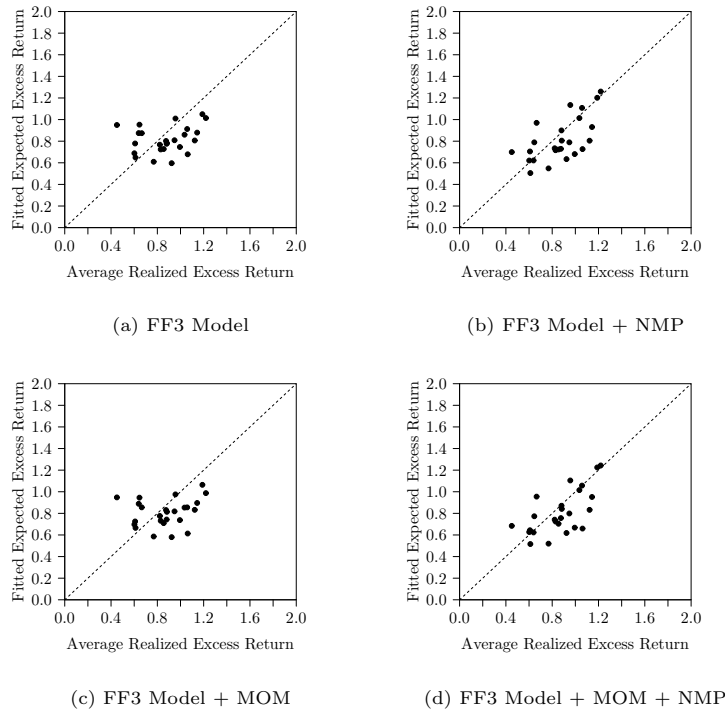


Figure 3: NMP and the Cross Section of Expected Excess Returns

In this figure, the model-predicted expected excess returns (vertical axis) for 25 test portfolios sorted by size and AHLG beta are plotted against the corresponding average realized excess returns (horizontal axis). Subfigures (a) and (c) show the Fama & French (1992) three-factor (FF3) model (Market, HML, SMB) and its extension with the Carhart (1997) momentum factor (MOM). Subfigures (b) and (d) show both models extended by NMP. The sample period is January 1995 to December 2020. The smallest pricing errors can be found along the dashed 45-degree line.

5.5. NMP Over Time

In addition to the multidecadal dynamics driven by the AMO (see Figure 1), 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 4 shows that the average excess returns of NMP in each quarter behave inversely to the corresponding hurricane arrival frequencies.³² 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).³³ 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 4) shows a significant negative coefficient for the third quarter.

We also 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.³⁴ The smooth series is plotted in Figure 5 a). We draw on the periodogram, the ACF and the PACF shown in Figure 5 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 4. 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.

³²We 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).

³³In line with recent results by Hassani & Yeganegi (2020), we run the Ljung-Box with a lag of 3.

³⁴This includes the current and previous two data points. The smooth quarterly series thus begins in Q3/1995.

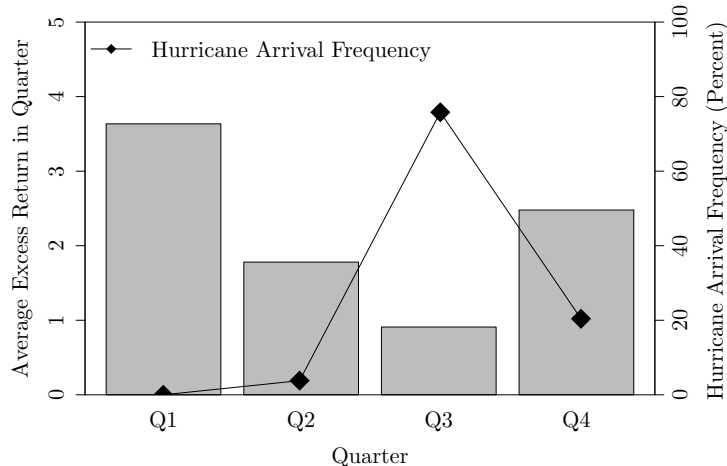


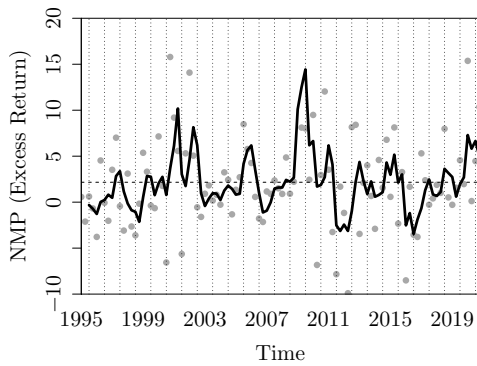
Figure 4: Quarterly Return Pattern of the Zero-Investment Portfolio NMP

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.

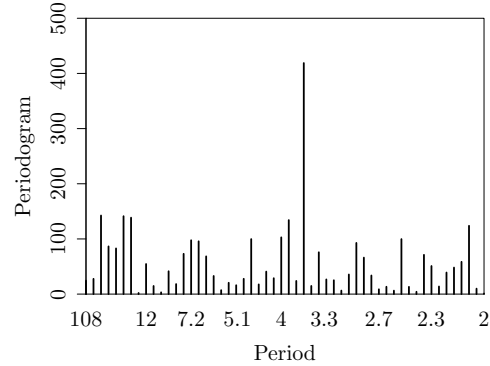
Panel a) TS Regression				Panel b) SARIMA (smooth NMP)			
	coeff.	p-val. (NW)	sig.		coeff.	p-val. (NW)	sig.
Intercept	1.0300	0.2784		AR(1)	0.2532	0.0105	**
Q2	-1.8547	0.1879		MA(1)	0.9350	0.0000	***
Q3	-2.7255	0.0321	**	MA(2)	1.0000	0.0000	***
Q4	-1.1560	0.3505		SAR(1)	0.3542	0.0004	***
df	75			df	98		
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 4: Time Series Analysis of the Zero-Investment Portfolio NMP

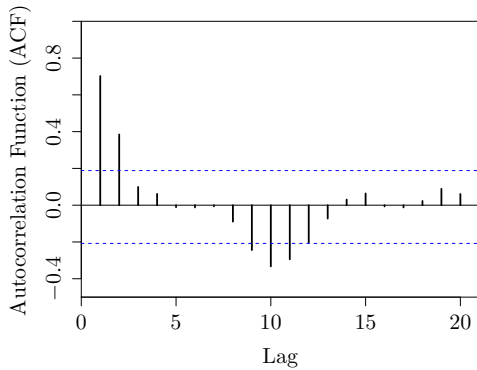
In Panel a), we report the coefficients (including intercept), p-values, significance levels and degrees of freedom (df) for a time series (TS) regression of the quarterly NMP series on dummy variables for the second, third and fourth quarter (first quarter forms the base category). We control for different 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 5. 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.



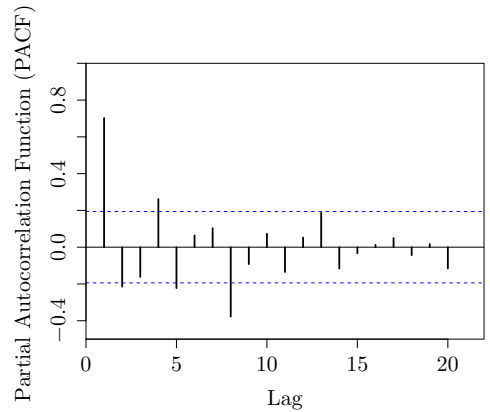
(a) NMP with Moving Average



(b) Periodogram



(c) ACF of NMP



(d) PACF of NMP

Figure 5: 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.

5.6. AHLG in the Excess Return Space

We additionally measure AHLG directly in the excess return space without the need for
460 a factor projection through a mimicking portfolio. In this regard, we take advantage of the
Swiss Re Cat Bond Performance Index [Bloomberg ticker: SRCATTRR]. Cat bonds are floating
rate notes that securitize various types of NatCat risk.³⁵ Cat bond investors obtain a pure play
exposure to the insured losses caused by natural disasters, of which hurricanes are by far the
most important type. Insured losses and economic losses are highly correlated³⁶ and cat bond
465 returns reflect seasonal and event-related changes in the underlying NatCat risk (Braun et al.,
2022). The Swiss Re Cat Bond Performance Index tracks all outstanding US-Dollar denominated
cat bonds, the vast majority of which references hurricane risk (Swiss Re, 2018).³⁷ Its monthly
return time series is therefore an ideal gauge for aggregate hurricane risk. Cat bond index
returns are available from February 1, 2002 to December 31, 2020. We turn them into excess
470 returns by subtracting the one-month T-Bill rates.

5.7. Cat Bond Betas and Univariate Sorting

We denote a firm’s cat bond beta β_i^{CAT} and estimate it on a monthly basis through the
following 36-month rolling regression, controlling for the Fama & French (1992) and Carhart
(1997) factors.³⁸ The cat bond betas need to be interpreted inversely to the AHLG betas. This
475 is because cat bonds experience negative returns in times of high hurricane risk.³⁹ Accordingly,
stocks of firms that suffer in the wake of hurricanes will exhibit a positive cat bond beta. On
the other hand, stocks of firms that benefit from hurricanes will have a negative cat bond beta.
If investors demand a hurricane risk premium, the former should earn higher future (excess)
returns than the latter. To examine this conjecture, we once more conduct univariate out-of-

³⁵For a detailed explanation of cat bonds see, e.g., Braun (2016).

³⁶For U.S. storm losses (adjusted to 2020 Dollars), the correlation amounted to 0.99 in the period from 1990
to 2020 (own estimate based on data from the Swiss Re Institute).

³⁷These comprise single-peril hurricane bonds or multiperil bonds with a significant fraction of expected loss
attributable to hurricane risk (Herrmann & Hibbeln, 2021; Braun et al., 2022)

³⁸The 36-month estimation window is selected because of the shorter time series of the cat bond index.

³⁹In the time period 2002–2017, the AHLG time series computed from Weinkle et al. (2018) losses and the
excess returns on the cat bond index exhibit a correlation of -0.53 .

480 sample portfolio sorts, this time for the period June 2006 to December 2020.⁴⁰

Table 5 shows the results for the value-weighted quintile portfolios.⁴¹ We report the portfolio that contains the stocks with the highest negative (positive) cat bond betas as portfolio 1 (portfolio 5) at the top (bottom). The row labeled 5–1 contains a zero-investment portfolio, which we will refer to as PMN (positive minus negative cat bond beta). Average betas are included in the first column and average excess returns in the second column. The remaining columns indicate the abnormal excess returns (alphas) that remain when regressing the excess return time series of the quintile portfolios on the capital asset pricing model (CAPM), the Fama & French (1992) factors and the Fama & French (1992) factors plus the Carhart (1997) momentum factor.

June 2006 to December 2020					
	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	-2.449	0.564%	-0.386%	-0.384%	-0.345%
2	-0.877	0.729%	-0.047%	-0.039%	-0.040%
3	+0.055	0.842%	0.069%	0.045%	0.045%
4	+1.032	1.019%	0.155%	0.105%	0.106%
Portfolio 5	+2.853	1.532%	0.419%	0.312%	0.314%
PMN (5–1)	5.302***	0.968%***	0.805%***	0.696%***	0.698%***
t-value	(2.024)	(3.440)	(2.911)	(2.955)	(3.120)

Table 5: Univariate Out-of-Sample Portfolio Sorts for Cat Bond Betas (Value Weighted)

This table shows the results for the out-of-sample portfolio sorts in the time period June 2006–December 2020. All portfolios are formed on a value-weighted basis. The portfolio with the highest positive cat bond betas is reported at the bottom. The row labeled PMN (5 – 1) contains the difference between the bottom and top quintiles. Average betas are included in the first and average excess returns in the second column. The remaining columns indicate the alphas that remain when regressing the excess return time series of the 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.

⁴⁰The time period for this analysis is determined by the availability of the cat bond index, which starts in February 2002. We then lose the first three years to the estimation window for the cat bond beta. Subsequently, we switch to June of the following year, applying the Fama & French (1992) convention that accounting data does not become available before then.

⁴¹Again, the results for equally-weighted portfolios can be found in the Appendix.

490 We observe considerable cross-sectional variation in the stocks' cat bond betas. Their aver-
ages range from -2.449 for portfolio 1 all the way up to $+2.853$ for portfolio 5. In line with this
observation, the average excess returns exhibit a clean monotonic increase from portfolio 1 to
portfolio 5. The zero-investment portfolio PMN has earned a highly significant average excess
return of 0.968 percent per month, which is equivalent to 11.616 percent per year. Even after
495 controlling for the three common asset pricing models in columns three to five, we are left with
a significant abnormal excess return of at least 0.696 percent or 8.352 percent p.a.

5.8. Fama & MacBeth (1973) Regressions

We now add multivariate evidence, using value-weighted Fama & MacBeth (1973) regressions
in the period from June 2006 to December 2020.⁴² Specifically, for each month t in the time
500 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 cat bond
beta, its log market capitalization (size), market beta, idiosyncratic excess return volatility,
coskewness with the market's excess return, book-to-market ratio, previous 12-month return
(past return), last-month return (reversal) and the Amihud (2002) illiquidity ratio. Table 6
505 presents the time-series averages of the monthly cross-sectional regression coefficients together
with Newey & West (1987) robust standard errors and significance levels.

The first column shows the effect of the cat bond beta in isolation. It confirms 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 cat bond betas earn higher future excess returns
510 than those with a negative cat bond betas. Economically, the latter act as a hurricane risk
insurance in an asset portfolio. The coefficient for the AHLG beta stays statistically significant
negative throughout.

5.9. Time Series Regressions

We continue by regressing the excess return time series of PMN on a comprehensive battery
515 of major factors from the extant asset pricing literature. We present the results of these analyses
in Table 7. Each model in columns one to five combines MKT, SMB, HML from Fama & French
(1992) plus MOM from Carhart (1997) with one additional factor. The extensions include the

⁴²With regard to the value-weighted Fama & MacBeth (1973) regressions, we follow Ang & Chen (2006). The
latter use the firms' market capitalizations at the beginning of each period for the weighting in cross-sectional
weighted least squares (WLS) regressions.

June 2006 to December 2020

	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$	$return_{(t+1)}$
β_i^{CAT}	0.15** (2.53)	0.14** (2.61)	0.13*** (2.75)	0.11*** (3.14)	0.12*** (3.14)	0.12*** (3.17)	0.12*** (3.26)	0.08** (2.47)	0.08** (2.49)
size		0.01 (0.21)	0.03 (0.62)	0.03 (0.58)	0.03 (0.58)	0.02 (0.35)	0.03 (0.58)	-0.01 (-0.08)	-0.01 (-0.12)
mkt-beta			0.23 (0.87)	0.23 (0.97)	0.24 (0.97)	0.22 (0.91)	0.22 (0.77)	0.18 (0.73)	0.17 (0.72)
idiosyncratic vola.			0.01	0.01 (0.09)	-0.01 (0.02)	-0.01 (-0.03)	-0.01 (-0.06)	-0.02 (-0.78)	-0.02 (-0.79)
coskewness					0.05 (0.22)	0.01 (0.02)	0.07 (0.28)	0.09 (0.39)	0.09 (0.36)
book-to-market						-0.31** (-2.51)	-0.29** (-2.43)	-0.27** (-2.29)	-0.35** (-2.33)
past return							-0.02* (-1.74)	-0.02* (-1.71)	-0.02* (-1.75)
reversal							0.29 (0.74)	0.27 (0.72)	
illiq									0.06 (0.97)
alpha	0.87** (2.44)	0.69 (0.80)	0.28 (0.45)	0.26 (0.34)	0.31 (0.40)	0.59 (0.86)	0.52 (0.77)	0.90 (1.47)	0.95 (1.59)

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

This table presents the results of multivariate value-weighted Fama & MacBeth (1973) regressions of excess returns in month $t+1$ on cat bond beta (β_i^{CAT}), size (log of market capitalization), market beta in month t (mkt-beta), idiosyncratic excess return volatility (idiosyncratic vol.), coskewness of the stock's excess returns with the market's excess returns (coskewness), book-to-market ratio (book-to-market), the past 12-month excess returns (past returns), last month return (reversal) and the Amihud (2002) illiquidity ratio (illiq). The sample period is June 2006 to December 2020. 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.

June 2006 to December 2020								
PMN	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1 MKT	0.158**	0.164**	0.079	0.159**	0.182	0.242**	0.204**	0.146*
1 SMB	0.144	0.133	0.034	0.127	0.095	0.141	0.183	0.031**
1 HML	-0.316***	-0.345***	-0.282**	-0.341***	-0.359**	-0.269***	-0.239	-0.326
1 MOM	-0.144	-0.146	-0.108	-0.146	-0.111			
2 PS		-0.017						
3 LOT			0.197**					
4 WTI				0.007				
5 BAB					-0.208***			
6 REVS						-0.195		
6 REVL						0.123		
7 RMW							0.199	
7 CMA							-0.030	
8 INV								0.123
8 ROE								-0.332*
alpha	0.698***	0.690***	0.842***	0.693***	0.739***	0.699***	0.640***	0.769***
t-value	(3.068)	(3.111)	(3.410)	(3.087)	(3.642)	(3.015)	(2.917)	(3.204)
R^2_{adj}	0.134	0.131	0.155	0.229	0.162	0.131	0.103	0.143

Table 7: Time Series Regressions of PMN (Value Weighted) on Established Factors

This table shows the results for eight time series regressions of PMN (value-weighted) on established factors. The sample period is June 2006 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 (5) enrich model (1) with: the Pástor & Stambaugh (2003) liquidity risk factor (PS), the Bali et al. (2011) lottery factor (LOT), the WTI oil index (WTI), and the Frazzini & Pedersen (2014) betting-against-beta factor (BAB). In models (6) through (8), 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).

Pástor & Stambaugh (2003) traded liquidity risk factor (PS), the Bali et al. (2011) lottery factor (LOT), the WTI oil index (WTI), the Frazzini & Pedersen (2014) betting-against-beta factor (BAB). Furthermore, in models six through eight, 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 eight cases, we are left with a statistically significant and economically large positive abnormal excess return of at least 0.640 percent per month (7.68 percent p.a.). As our zero-investment portfolio of stocks with positive minus negative cat bond betas withstands this broad range of established factor model specifications, carries additional systematic risk information so far not explicitly carved out in the literature.

5.10. Geographic versus Economic Hurricane Risk Exposure

Having estimated the hurricane risk premium predicted by our theory, we now determine how it relates to 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 and shocks from natural disasters have been shown to strongly propagate through production networks (Cohen & Frazzini, 2008; Barrot & Sauvagnat, 2016).⁴³ Hence, hurricanes can affect firms far away from their actual landfall location, which 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

⁴³In 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.

headquarter state of all firms, which mentioned *hurricane loss* at least once in in their publicly available financial reports. Figure 6 illustrates the results in comparison to a NOAA map that shows the landfall states of all hurricanes between 1815 and 2012. 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 physically disconnected from the actual 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 losses. Subsequently, we repeat the univariate sorting using cat bond betas 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 8 summarizes the results. The average excess return of the PMN portfolio (5-1) in the subsample of states with firms that reported hurricane losses (Panel a) amounts to a positive and significant 1.117 percent per month (13.404 percent p.a.). In contrast, the PMN portfolio formed from stocks in the remaining states without reports of hurricane losses (Panel b)) turns out to be insignificant. This highlights that economic rather than geographic exposure is the relevant basis for the hurricane risk premium.

5.11. *Hurricane Risk Across Economic Sectors*

In a last step, we explore the hurricane risk premium across economic sectors. To this end, we split our sample of firms along the North American Industry Classification System (NAICS) into primary, secondary and tertiary sectors and sort the stocks in each subsample based on their cat bond beta. According to the NAICS, the primary sector consists of agriculture, forestry and fishing (NAICS 11). The secondary sector comprises the mining, electricity, water and gas supply, construction, and manufacturing industries (NAICS 12-41). The tertiary sector consists of a large range of service industries, including, amongst others, transportation, financial services and insurance, real estate and property, entertainment and recreation, as well as accommodation and food/beverage (NAICS 42-92). We find significant hurricane risk premiums for the

Panel a) Headquarters with Hurricane					
	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	-2.546	0.487%	-0.514%	-0.518%	-0.476%
2	-0.894	0.729%	-0.0859%	-0.076%	-0.077%
3	+0.093	0.900%	0.0875%	0.019%	0.019%
4	+1.123	1.076%	0.221%	0.134%	0.134%
Portfolio 5	+2.985	1.603%	0.492%	0.344%	0.345%
PMN (5-1)	+5.531***	1.117%***	1.005%***	0.863%**	0.863%***
t-value	(2.781)	(3.461)	(3.011)	(2.901)	(2.915)

Panel b) Headquarters without Hurricane					
	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	-2.331	0.769%	-0.088%	-0.058%	-0.025%
2	-0.837	0.749%	0.006%	0.002%	0.002%
3	+0.023	0.766%	0.055%	0.076%	0.076%
4	+0.914	0.897%	0.029%	0.069%	0.071%
Portfolio 5	+2.681	0.950%	-0.089%	-0.006%	-0.003%
PMN (5-1)	5.012***	0.174%	0.009%	0.059%	0.064%
t-value	(36.849)	(0.693)	(0.044)	(0.256)	(0.331)

Table 8: Value-Weighted Sorting on Cat Bond Betas for Sample Split Along Economic Exposure

This table shows the results for the out-of-sample portfolio sorts on cat bond betas for the period between June 2006 to December 2022. 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, MA, 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. All portfolios are formed on a value-weighted basis. The portfolio with the highest positive hurricane risk betas is reported at the bottom. The row labeled NMP (5 - 1) contains the difference between the bottom and top 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.

secondary and tertiary sectors. The respective results are summarized in Table 9.⁴⁴ Evidently, the hurricane risk premium is notably larger for the secondary sector. This implies that manufacturing rather than service-related industries are more strongly exposed to hurricane risk, most likely through their supply chain networks.

We complement these findings with anecdotal evidence from the annual 10-K reports of exemplary companies, which can be found in Tables 10 (secondary sector) and 11 (tertiary sector). These extracts illustrate how hurricanes have impacted firms in various lines of business.

	Secondary Sector			Tertiary Sector		
	Av. Beta	Av. Exc. Return	Carhart-Alpha	Av. Beta	Av. Exc. Return	Carhart-Alpha
Portfolio 1	-2.585	0.510	-0.310	-2.301	0.748	-0.141
2	-0.844	0.740	0.014	-0.912	0.694	-0.137
3	+0.073	0.793	0.164	+0.029	0.874	0.043
4	+1.068	0.852	-0.062	+0.987	1.041	0.152
Portfolio 5	+3.092	1.606	0.418	+2.601	1.373	0.366
PMN (5-1)	5.676***	1.096***	0.775**	4.903***	0.625***	2.679**
t-value	3.835	3.319	2.204	2.273	2.889	2.944

Table 9: Value-Weighted Sorting on Cat Bond Betas for Sample Split Along Economic Sectors
This table shows the results for the out-of-sample portfolio sorts on cat bond betas within industry sectors in the time period June 2006–December 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 PMN (5 – 1) contains the difference between the bottom and top quintiles. Average betas are included in the first and average excess returns in the second column. The third column contains the alphas that remain when regressing the the portfolios on the Fama & French (1992) and Carhart (1997) factors. ***, ** and * indicate significance at the one, five, and ten percent levels.

Finally, we summarize insights from extant research that highlights the links between hurricane risk and secondary as well as tertiary sector firms. Manufacturing businesses may 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). For the construction sector, there is evidence for post-event demand-surge effects (see Döhrmann et al., 2017). However, there are also indications for reductions in the profitability of construction firms following major hurricanes. Hsiang (2010), e.g., report a positive growth effect for the sector, but significantly higher labor costs. Similarly, Belasen & Polachek (2008) show that average worker earnings in hurricane struck counties tend to rise. Vigdor (2008) reports an

⁴⁴The results for the primary sector without significant effects are available from the authors upon request.

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

A significant hurricane risk premium for tertiary sector firms is also plausible. Property-
casualty insurers are often particularly exposed to natural disaster risk (Lamb, 1995) and recent
work has documented that this impacts their costs of capital (Ben Ammar et al., 2018). There
605 is also evidence of adverse effects on banks (Schüwer et al., 2019) and Real Estate Investment
Trusts (Rehse et al., 2019). Moreover, service-related industries contract when public life comes
to a halt after the disaster (Vigdor, 2008). A particularly vulnerable business sector in this
regard is the tourism industry, which may also be hit by the destruction of key accommodation
and transportation infrastructure.

610 **6. 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 in the spirit of Constantinides & Duffie (1996), we identify two conditions
for a hurricane risk premium in the cross-section of stock returns. The first condition demands
615 that AHLG is positively correlated with the variance of state-level consumption growth; the
second condition states that an asset’s return is negatively related to AHLG.

We examine both theoretical conditions for a hurricane premium in the cross section of stock
returns empirically. Our results reveal that the correlation between AHLG and the variance
of state-level income growth (as a proxy for consumption inequality) is significantly positive
620 from 1995 to 2020, a period that is characterized by increased hurricane losses. For the same
period, we find that stocks with a negative sensitivity to hurricane risk have larger future
returns than stocks with a positive sensitivity. This hurricane premium is statistically significant
at the 1% level and amounts to more 11 percent p.a. The premium is neither explained by
traditional asset pricing risk factors nor firm characteristics, such as size, idiosyncratic volatility
625 or coskewness. Turning to drivers of the hurricane risk premium, we analyze firms’ actual

Industry	Company name	Extract of Annual Reports (10-K)
Manufacturing	Mosaic Co (10-K filed on August 11, 2006)	“During the 2004 hurricane season, three hurricanes impacted our central Florida processing facilities and mining operations, resulting in certain releases of phosphoric acid process wastewater and storm water into the environment.”
	Modine Manufacturing Company (10-K EX-13 filed on May 30, 2007)	“In addition, strong coil and condenser sales, especially in southeastern portions of the U.S. related to Hurricane Katrina, also contributed to the fiscal 2006 increase in net sales.”
Construction	M/I Homes (10-K EX-13 filed on February 16, 2018)	“For example, in September 2017, Hurricane Harvey and Hurricane Irma caused disruption and delays in our Houston and Florida markets, which may continue to impact results in these markets in fiscal 2018.
	Dycom Industries Inc (10-K filed on September 7, 2007)	“During fiscal year 2006, we earned approximately \$61.1 million from hurricane restoration services for telecommunications customers.”

Table 10: Hurricane Risk Examples from the Secondary Sector

This table presents selected examples of hurricane risk affecting the economic performance of companies, as stated in their public financial statements from the United States Securities and Exchange Commission.

Industry	Company name	Extract of Annual Reports (10-K)
Accommodation and Food Services	Park Hotels and Resorts Inc (PK) (10-K EX-13 filed on February 28, 2019)	“For example, in 2017, Hurricane Irma forced us to close two of our hotels in Key West, Florida for several weeks, and Hurricane Maria caused significant damage to the Caribe Hilton in Puerto Rico, which was closed throughout 2018. ”
	Hilton Worldwide Holdings Inc. (10-K filed on February 13, 2019)	“RevPAR (Revenue Per Available Room) growth in the U.S. was driven by increased demand in certain markets as a result of hurricane relief efforts.”
Financials	FG Financial Group, Inc. (10-K filed on March 26, 2018)	“For example, in late August 2017, Hurricane Harvey made landfall in Louisiana and Texas, impacting many of our policyholders. [...] We expect our total gross incurred losses for Hurricane Harvey to be approximately \$27,000,000 [...].
	PXRE Group Ltd. (10-K filed on March 16, 2006)	“As a result of the unprecedented size of the industry-wide losses from Hurricanes Katrina, Rita and Wilma, rates and limitations in coverage are expected to be favorable for each of the lines of business that we underwrite in 2006.”

Table 11: Hurricane Risk Examples from the Tertiary Sector

This table presents selected examples of hurricane risk affecting the economic performance of companies, as stated in their public financial statements from the United States Securities and Exchange Commission.

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 firms in those states that were (economically) affected by hurricane losses in the past, and, hence, show an increased likelihood for being hit in the future. We also document that the excess return time series of our zero
630 investment portfolio follows the same seasonal pattern as the underlying hurricane risk itself. Finally, the hurricane risk premium exists for the secondary and tertiary sectors, which both exhibit plausible exposures to hurricane risk.

This study uncovers an economic channel through which natural disaster risk feeds into financial markets. We provide strong empirical evidence that firms that are threatened by
635 (uninsured) hurricane risk exhibit higher cost of equity than their unexposed peers. It can be expected that climate change will further exacerbate the compensation for atmospheric perils demanded by investors. How companies can react to this climate risk exposure is an interesting topic for future research.

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7. Appendix

925 7.1. 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 ($E[X] = E[Y] = E[Z] = 0$) and unit variance ($E[X^2] - E[X]^2 = E[Y^2] - E[Y]^2 = E[Z^2] - E[Z]^2 = 1$). This can always be achieved by demeaning and standard-
930 izing 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 :

$$X = aY + X^*, \quad (11)$$

$$Z = bY + Z^*. \quad (12)$$

The expectation of X times Y is

$$\begin{aligned} E[XY] &= E[(aY + X^*)Y] & (13) \\ &= aE[Y^2] + E[YX^*], \end{aligned}$$

and the expectation of Z times Y equals

$$\begin{aligned} E[ZY] &= E[(bY + Z^*)Y] & (14) \\ &= bE[Y^2] + E[YZ^*]. \end{aligned}$$

$E[YX^*]$ and $E[YZ^*]$ are zero by design. Recall that X and Y have zero means and unit variances, implying that their standard deviations are $\sqrt{E[X^2]} = 1$ and $\sqrt{E[Y^2]} = 1$. Consequently, a and b represent the correlations between X and Y ($\rho[X, Y]$) as well as Z and Y ($\rho[Z, Y]$):
935

$$a = E[XY] = \frac{E[XY]}{\sqrt{E[X^2]} \cdot \sqrt{E[Y^2}}} = \rho[X, Y], \quad (15)$$

$$b = E[ZY] = \frac{E[ZY]}{\sqrt{E[Z^2]} \cdot \sqrt{E[Y^2}}} = \rho[Z, Y]. \quad (16)$$

Next, we derive the variances of X^* and Z^* . To this end, first rewrite the variances of X and Z , using (11) and (12):

$$\begin{aligned} \mathbb{E}[X^2] &= a^2\mathbb{E}[Y^2] + 2a\mathbb{E}[YX^*] + \mathbb{E}[X^{*2}] \\ &= a^2 + \mathbb{E}[X^{*2}] = 1, \end{aligned} \quad (17)$$

940

$$\begin{aligned} \mathbb{E}[Z^2] &= b^2\mathbb{E}[Y^2] + 2b\mathbb{E}[YZ^*] + \mathbb{E}[Z^{*2}] \\ &= b^2 + \mathbb{E}[Z^{*2}] = 1. \end{aligned} \quad (18)$$

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

$$\mathbb{E}[X^{*2}] = 1 - \rho[X, Y]^2, \quad (19)$$

$$\mathbb{E}[Z^{*2}] = 1 - \rho[Z, Y]^2. \quad (20)$$

Finally, inserting $a = \rho[X, Y]$ and $b = \rho[Z, Y]$ in (11) and (12) and taking the expectation of X times Z , delivers the correlation of X and Z ($\rho[X, Z]$) as a function of $\rho[X, Y]$ and $\rho[Z, Y]$:

$$\begin{aligned} \rho[X, Z] &= (\mathbb{E}[XZ] - \underbrace{\mathbb{E}[X] \cdot \mathbb{E}[Z]}_{=0}) / \underbrace{\sqrt{(\mathbb{E}[X^2] - \mathbb{E}[X]^2) \cdot (\mathbb{E}[Z^2] - \mathbb{E}[Z]^2)}}_{=1}} \\ &= \rho[X, Y] \cdot \rho_t[Z, Y] \cdot \mathbb{E}[Y^2] + \rho[X, Y] \cdot \underbrace{\mathbb{E}[YZ^*]}_{=0} \\ &+ \rho[Z, Y] \cdot \underbrace{\mathbb{E}[YX^*]}_{=0} + \mathbb{E}[X^*Z^*] \\ &= \rho[X, Y] \cdot \rho[Z, Y] + \mathbb{E}[X^*Z^*]. \end{aligned} \quad (21)$$

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

$$\mathbb{E}[X^*Z^*] = \rho[X^*, Z^*] \sqrt{\mathbb{E}[X^{*2}] \cdot \mathbb{E}[Z^{*2}]} + \mathbb{E}[X^*] \cdot \mathbb{E}[Z^*]. \quad (22)$$

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

7.2. Sorting Results for Equally-Weighted Portfolios

955 Below, we report the results for the univariate sorting into equally-weighted quintile portfolios both based on cat bond betas (Table 13) and based on AHLG betas (Table 12). In both cases, the hurricane risk premium persists in the post 1995 period, but turns out to be of a smaller size.

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 (5-1)	-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 (5-1)	-5.382***	0.528%***	0.405%***	0.379%**	0.469%***
t-value	(-142.65)	(3.460)	(2.671)	(2.617)	(3.004)

Table 12: Univariate Out-of-Sample Portfolio Sorts for AHLG Betas (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.

February 2002 to December 2020					
	Av. Beta	Av. Return	CAPM-Alpha	FF3-Alpha	Carhart-Alpha
Portfolio 1	-3.439	0.668%	-0.403%	-0.206%	-0.204%
2	-0.935	0.822%	-0.159%	0.032%	0.034%
3	+0.039	0.892%	-0.067%	0.115%	0.116%
4	+1.059	0.968%	-0.060%	0.121%	0.124%
Portfolio 5	+3.809	0.975%	-0.184%	0.029%	0.034%
PMN (5-1)	7.249***	0.307%***	0.219%***	0.235%***	0.237%***
t-value	(39.303)	(2.322)	(1.686)	(1.737)	(2.173)

Table 13: Univariate Out-of-Sample Portfolio Sorts for Cat Bond betas (Equally Weighted)

This table shows the results for the out-of-sample portfolio sorts in the time periods February 2002– December 2020. All portfolios are formed on a value-weighted basis. The 3% of the smallest market capitalisation firms in the monthly cross-section are excluded. The portfolio with the highest positive cat bond risk betas is reported at the bottom. The row labeled PMN (5 – 1) contains the difference between the bottom and top 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.