Pricing Physical Climate Risk in the Cross-Section of Returns*

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Abstract

Using location-specific climate exposure measures, I test for the existence of physical climate risk premia. Hurricane risk commands a positive risk premium whilst heat stress commands a negative risk premium. Both exposure to sea-level rise and exposure to extreme rainfall command no risk premium. The priced portion of physical climate risk is only between 8% - 38% of its total variance. The *unpriced* portion co-varies with fundamental risks in the economy, suggestive of agents struggling to price a material risk, and the unpriced portion can be explained by industry returns and the realisation of severe weather events.

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1 Introduction

The Task Force on Climate-related Financial Disclosure (TCFD; 2017, p.3) views climate change as one of the "most misunderstood risks that organisations face today" and institutional investors believe physical climate risks[1] are under-priced (Krueger et al.; 2020). Meanwhile, according to a survey by the World Resources Institute, it is "unlikely that publicly available guidance fully equips companies and financial organizations to assess the range of potential physical climate hazards documented by climate science" (Pinchot et al.; 2021, p.2). Such confusion supports claims that the *translation* of climate science into actionable information for non-experts is difficult or even misleading, meaning it is also unclear if physical climate risk is priced as a systematic risk factor (Fiedler et al.; 2021; Pitman et al.; 2022)[2].

I make two contributions. First, I construct new and specific physical climate risk factors that span a 10-year period. Exposure to sea-level rise, hurricanes/tropical cyclones, heat stress, and extreme rainfall are proxied by separate tradeable risk-factor-mimicking portfolios that are dynamically constructed at each period for the US equity market. These factors use firm-level physical climate risk scores obtained from *Four Twenty-Seven*, who assess *facility-level* exposure to various physical climate risks in a forward-looking manner before aggregating to a firm-level score. Such data potentially improves on measures that rely on firm disclosures, news, the location of headquarters, or attempts to aggregate physical climate risk with other topics such as collating environmental, social, and governance factors when building ESG scores.

Second, I explicitly test whether measurement error in a candidate physical climate risk factor is due to noise or mispricing. The key to doing this is to view a candidate risk factor as comprising of two parts: a priced portion that agents view as a systematic risk and an unpriced portion that is not associated with any return premium. Usually, these two portions are assumed to be unrelated (e.g., Giglio and Xiu, 2021). My contribution is to explicitly test this assumption. If agents are unable to price a systematic risk, despite it being related to returns or other priced factors, then it should appear in an asset-pricing model and not treated as an ignorable term.

[1] Physical climate risk is defined as acute event-driven risks, including the increased severity of extreme weather events such as floods and hurricanes, and chronic long-term shifts in climate patterns, such as sea-level rise and average temperatures, that can directly damage assets (TCFD; 2017). The focus of this paper is on direct operational risks.

[2] For example, temperature extremes appear not to affect sales for US firms on aggregate (Addoum et al.; 2020), implying agents can easily hedge these risks through diversification.

I identify a statistically significant risk premium for hurricane risk of 0.39% per month and for heat stress of -0.59% per month when estimated using realised returns. This result also holds for hurricane risk when using an expected return proxy. The risk premium for heat stress using an expected return proxy is negative but very close to zero. There is no significant risk premium associated with exposure to sea-level rise and extreme rainfall when using realised returns. For comparison, the estimated monthly risk premium for the market factor over the sample is 1.12% per month. The priced portion of time-series innovations in the physical climate risk factors is only between 8% - 38% of the total variance compared to approximately 100% for the market, size, value, and investment factors. Crucially, there is evidence that this is not due to noise, i.e., classical measurement error, since the errors in the physical climate risk factors co-vary significantly with priced latent factors that capture risks in the economy. The conclusion is that there exists some common variation that drives physical climate risk without being priced. Common risk factors, industry portfolio returns, and the *realisation* of severe weather events are all found to be able to explain the mispricing errors in the physical climate risk factors, providing preliminary backing for the hypothesis that agents do not fully price material physical climate risks.

I contribute to various strands of literature. First, a growing literature constructs risk-factor-mimicking portfolios for physical climate risks to estimate whether exposure to such a risk can explain the cross-section of returns. In this paper, I provide four new, and separate, physical climate risk factors built from wide-ranging exposure scores that rely on *facility*-level climate information[3] and utilise a cross-sectional approach to construct the factors (Fama and French; 2020). In related work, Hong et al. (2019) build an equal-weighted portfolio from drought risk exposure that buys food stocks in countries with a positive drought trend and sells those with a negative drought trend. Their results imply investors under-react to drought risk as the strategy commands a negative premium of -0.19% per month. Sautner et al. (2022) build similar long-short portfolios derived from the proportion of earnings calls spent discussing physical climate risks but find no significant premium when assessing realised returns. Nagar and Schoenfeld (2022) and Faccini et al. (2021) build long-short portfolios from annual report disclosures and news, respectively, and identify a significantly positive premium of 0.20% per month and 0.27% per month, respectively. Braun et al. (2021) form long-short

[3] I make available the time-series return of the constructed factors at https://www.sites.google.com/view/glengostlow/datacode.

portfolios using the slope coefficient of returns regressed on aggregate hurricane loss growth and identify a significantly positive premium (0.74% per month), with similar risk premia found in this paper despite using a completely new source of data and a different empirical approach. Acharya et al. (2022) and Sautner et al. (2022) both construct firm-level *expected* return proxies to assess the pricing of physical climate risk. They identify a positive risk premium for heat stress after 2013 and an insignificant risk premium for other physical climate risks, and an insignificant positive premium for attention to physical climate risk, respectively[4].

The second, and most important, strand of literature this paper relates to is the issue of translating climate science into decision-useful information. Knowledge across various spatial and temporal time-scales is required to assess exposure and, importantly, the materiality of physical climate risks. Compounding this difficult task is the fact climate scientists have high confidence in the thermodynamic aspects of climate change (e.g. "the earth is warming"), yet much lower confidence in dynamic aspects (e.g. "where and how strong a storm is") (Shepherd et al.; 2018). Excessive trust can then be placed in vague long-term climate predictions that may not contain an exhaustive set of possible material risks (Fiedler et al.; 2021)[5]. This paper contributes to this literature by assessing whether agents price physical climate risk as a systematic risk factor and, if not, whether the unpriced portion of the factor is noise (measurement error) or mispricing. My contribution is that the unpriced portions of four physical climate risk factors appear related to priced fundamental risks in the economy, suggestive of mispricing. Indeed, this unpriced component captures 62-92% of the variation in the physical climate risk factors. I take this as evidence that agents are struggling to price material physical climate risks and conjecture that this occurs due to the issue of translating climate science into decision-useful information. Indeed, agents expect no difference in expected returns between stocks exposed to heat stress and safe stocks, yet the realised return of a heat stress factor is negative even after controlling for unexpected extreme temperature news - suggestive of mispricing.

[4]Interestingly, Acharya et al. (2022) also utilise firm-level data from *Four Twenty-Seven* as in this paper. Sautner et al. (2022) claim to identify a significantly positive risk premium for attention to physical climate risk when scores are aggregated at the industry level, arguing this is due to the fact the industry physical climate risk measure is less sparse than its firm-level equivalent.

[5]Such risks may also be idiosyncratic and dynamic: they change depending on a firms' resilience and on climate dynamics (Freiberg et al.; 2020). See also Pitman et al. (2022) for a discussion on the uncertainties of material physical climate risk exposure that arise from the use of climate models.

Relatedly, the third strand of literature this paper contributes to is the issue of measurement error, more broadly, in asset-pricing. Measurement error, or noise, is the unpriced component of a candidate risk factor that "may be interesting in its own right, but is not likely to be a central puzzle in the intersection of macroeconomics and finance" (Clarke; 2022, p.161) due to the simple fact it is not priced by agents. Clarke (2022), Giglio and Xiu (2021), and Daniel et al. (2020) all provide a similar framework for the problem: disentangle the priced and unpriced components of a candidate risk factor and view the unpriced component as noise. However, they stop short of testing explicitly if both components are related. In this paper, I disentangle the priced and unpriced portion of candidate physical climate risk factors and, as different from the extant literature, acknowledge that as long as the unpriced portion of a factor co-varies with priced latent factors, then non-classical measurement error exists and, due to omitted variable bias, indicates error by agents rather than by the researcher. Indeed, I find that the unpriced component *is* significantly associated with the priced component, but this result only holds for physical climate risk factors and not the Fama and French (2015) five-factors - which I use as a benchmark.

2 Theory and Risk Factor Construction

To determine the expected sign of the physical climate risk premium, a theoretical asset-pricing model with climate risk proposed by Pástor et al. (2021) is provided to guide the analysis[6].

First, assume agent i has exponential utility:

$$V(\tilde{W}_{i1}, X_i, \tilde{C}) = -e^{-A_i \tilde{W}_{i1} - b_i X_i - c_i \tilde{C}}, \tag{1}$$

where $\tilde{W}_{i1}$ is wealth in period 1, X_i is a $N \times 1$ vector that contains the fraction of the agent's wealth invested in each stock, $\tilde{C}$ is the stability of the climate, A_i is absolute risk aversion, b_i is the non-pecuniary benefit from holding stocks, and c_i is the climate sensitivity of agent i[7].

[6]Whilst I use the model proposed by Pástor et al. (2021) to provide a sign to the physical climate risk premium, alternative approaches are discussed in Giglio, Kelly and Stroebel (2021) that alter the expected sign of the risk premium.

[7]Climate sensitivity in this context is different from its definition in climate economics. The latter uses climate sensitivity to mean the average global temperature rise from a doubling of CO2 concentration in the atmosphere. In this case, it means how sensitive the agent's utility is to the climate.

The wealth-weighted mean of climate sensitivity across agents is given by $\bar{c}$ and is strictly positive, such that a stable climate is preferred by the *average* agent. Agents prefer a stable climate because severe weather events are less damaging, or even absent, in this state. The exposed assets are therefore riskier and must offer agents a higher expected return to hold them.

Given this, what do we learn about the sign of the expected physical climate risk premium? In equilibrium, we would expect a portfolio that has a higher exposure to some risk to have a higher return. Assuming that physical climate risk can be proxied by the variable g, climate sensitivity $\bar{c}$ drives the performance of a physical climate risk factor g and is strictly positive[8]. The intuition for this result is relatively straightforward. Physical climate risk increases risk for exposed assets; these assets may then suffer losses, have decreased earnings, or go bankrupt due to operational issues caused by severe weather events. Agents dislike such events because it lowers their total wealth. The expected performance of, or the returns to, the factor should therefore be positive on average: agents are compensated with greater expected returns if they hold assets that co-vary positively with physical climate risk. Thus:

$$\bar{c} \equiv g > 0. \tag{2}$$

The mechanism behind the physical climate risk factor is much like other rational asset-pricing stories such as the risk of bankruptcy for small-cap stocks. The earnings prospects of small-cap stocks are more sensitive than large-cap stocks, a feature that agents dislike, which leads to a distress factor that is priced in returns (Fama and French; 1993, 1996; Chan and Chen; 1991). However, unlike the measurement of small-cap stocks, physical climate risk is notoriously difficult to estimate, especially at the firm-level, leading to unclear and potentially mismeasured physical climate risk premia.

[8]See Pástor et al. (2021).

2.1 Building the Physical Climate Risk Factor

I now build the physical climate risk factor. The canonical approach to represent a candidate risk factor, first posited by Black et al. (1972) and popularised by Fama and French (1993), involves identifying tradeable assets with high and low exposures to a characteristic and then forming value-weighted long-short portfolios. Whilst this approach has dominated the empirical asset-pricing literature, the method offers many degrees of freedom to the researcher (Jensen et al.; 2021).

Fama and French (2020) show that a cross-sectional approach, that weighs assets by a characteristic of interest at each time t, dominates the long-short portfolio approach because of the ability to neutralize exposure to other risk factors and to more closely relate to theory[9]. An important benefit is the ability to utilise the period-by-period predictive power of a *firm-level* characteristic of interest whilst controlling for time-varying characteristics, as adopted in similar papers by Pástor et al. (2022), Lioui and Tarelli (2022), and Bolton and Kacperczyk (2021).

The necessary inputs to construct such a cross-sectional factor include a vector of cross-sectional firm-level physical climate risk scores $\boldsymbol{\psi_t}$ and a vector of cross-sectional excess stock returns $\boldsymbol{r_t}$ measured at each period t. The sample of stocks at each time period t is given as N_t, such that $\boldsymbol{r_t} = [r_i, ..., r_N]$ and $\boldsymbol{\psi_t} = [\psi_i, ..., \psi_N]$. Notice that this means the set of stocks used at each time period can be different[10]. Following Fama and French (2020) and Lioui and Tarelli (2022), I de-mean the physical climate risk scores at each period so that they sum to zero.

The scores are time-invariant, reflecting the premise physical climate risk is relatively stationary (i.e., the raw physical climate risk score for each firm is the *same* across all periods). Nagar and Schoenfeld (2022, p.4) provide anecdotal evidence that this is true over a number of years. In related work, Acharya et al. (2022) and Ginglinger and Moreau (2022) both utilise data from *Four Twenty-Seven*, which I also use, and argue the scores are accurate across medium time horizons such as 10 years. Regardless, to mitigate potential concerns with this assumption, I only include firms in the sample if their geographical revenue exposure has

[9] See Lioui and Tarelli (2022) for a review of this matter related to "green" factors.

[10] In practice, the reason why a stock may be in the sample in one period and not the next is due to 1) its market capitalisation being below the threshold used to exclude small-cap stocks and 2) it not being traded at the time of inclusion in the sample.

not changed by more than 90% from when the *Four Twenty-Seven* data was obtained. I detail this more fully in Section 4.3.

The following cross-sectional regression is then estimated at each time t:

$$\boldsymbol{r}_t = a_t + g_t \boldsymbol{\psi_t} + \boldsymbol{\epsilon}_t, \tag{3}$$

where $t \in [0, T]$, a_t is the intercept, g_t is the proxy variable for exposure to physical climate risk, $\boldsymbol{\psi_t}$ is the vector of cross-sectional firm-level physical climate risk scores, and $\boldsymbol{\epsilon_t}$ is the error term[11]. The return of the physical climate risk factor at each period t is $\widehat{g}_t$, estimated from Eq. 3, and the weight given to each firm in the portfolio is given by its physical climate risk score. Firms with a negative de-meaned physical climate risk score have negative weights in the portfolio and firms with a positive de-meaned physical climate risk score have positive weights in the portfolio. This approach results in a zero-investment portfolio where the risk-factor-mimicking portfolio has unit exposure to physical climate risk. The vector $\boldsymbol{g} = [\hat{g}_0, ..., \hat{g}_T]'$ shall be used to denote the estimated time-series innovations in the candidate physical climate risk factor. The Appendix provides further details on the approach.

[11] I also construct a cross-sectional market factor in a similar fashion by replacing $\boldsymbol{\psi_t}$ in Eq. 3 with each stock's de-meaned market beta in the previous period, estimated via rolling 12-month regressions of each stock's excess return on the excess market factor. Constructing cross-sectional factors ensures the physical climate risk factors are put on an equal footing with other risk factors when used in the same regression. I thank Abraham Lioui for this insight. The market factor is also constructed so that it has unit variance.

3 Empirical Strategy

I now provide the approach to estimate the premium associated with exposure to physical climate risk.

3.1 The Three-Pass Procedure

I first assume a linear asset-pricing model that says the time-series excess return of asset j, $\boldsymbol{r_j}$, depends on exposure to priced risk factors and *potentially* physical climate risk. The aim of the candidate factors is to explain why some assets earn greater returns than others. The physical climate risk factor is constructed following the approach in Section 2.1 and denoted $\boldsymbol{g}$. For simplicity, each other priced risk in the economy is given as $\boldsymbol{f_\kappa}$, where $\boldsymbol{f_\kappa} : [1, K]$[12]. Then:

$$\boldsymbol{r_j} = q_j + \beta_j \boldsymbol{g} + \sum_{\kappa=1}^{K} \beta_{\kappa,j} \boldsymbol{f_\kappa} + \boldsymbol{\epsilon_j}, \quad i.i.d.\ \boldsymbol{\epsilon_j} \sim \mathcal{N}(0,1), \tag{4}$$

where q_j is the intercept, β_j is exposure to a potentially priced candidate physical climate risk factor $\boldsymbol{g}$, and $\boldsymbol{\epsilon_j}$ is the error term[13]. Eq. 4 is a model to identify risks that exposed agents should be compensated for, where I am interested in whether exposure to physical climate risk compensates agents as theory would suggest (Pástor et al.; 2021). Two common approaches to estimate Eq. 4 include the Fama and MacBeth (1973) two-pass procedure that first estimates each stock's loading on candidate risk factors before estimating a time-series regression of stock returns on these estimated loadings, and a simple regression of the candidate factor on common risk factors (where a significant alpha provides evidence for a new priced risk). However, two potential issues arise that motivate my empirical strategy[14].

First, the asset-pricing model is usually determined a-priori. Eq. 4 states that asset j's outperformance is due to its exposure to undiversifiable risks. However, fully specifying such an asset-pricing model is difficult owing to the plethora of identified risk factors (Cochrane; 2011). I could arbitrarily test a model with only the market factor, with three-factors (Fama and French; 1993), with five-factors (Fama and French; 2015),

[12] Later in this section, it will be shown that $\boldsymbol{f_\kappa}$ are estimated as latent factors.

[13] It is common to utilise portfolios as the test assets $\boldsymbol{r_j}$ in order to combat the errors-in-variables problem; where the betas in Eq. 4 are estimated with some degree of error that is attenuated when using individual assets (Jensen et al.; 1972). Consequently, I also use portfolios.

[14] In the results, I begin by regressing the physical climate risk factor on a market factor and then, as robustness to my main result, estimate Fama and MacBeth (1973) regressions. Given the issues discussed later in Section 3, the results focus on the three-pass procedure.

or many more (Harvey et al.; 2016). As long as an omitted factor is correlated with a candidate factor and asset j, the estimated premium associated with a unit exposure to the candidate factor will be biased[15]. In reality, the literature is infant regarding the link between physical climate risk and other risk factors, implying a high chance of omitted variable bias.

Second, an issue arises with the measurement of the candidate physical climate risk factor itself. Agents may perceive, and thus price, risk from a constructed factor very differently to the true factor. The researcher, however, assumes such a factor is constructed accurately and incorrectly draws the conclusion that the factor commands small or no compensation for a unit of exposure to it. This is an issue, generally, in the asset-pricing literature (Giglio and Xiu; 2021), but is more likely for physical climate risk given the difficulties in estimating exposure (e.g., see Berg et al., 2022).

Following Giglio and Xiu (2021), I capture the idea of omitted factors and measurement error with the following intuition. Assume a candidate risk factor is comprised of two parts: a priced portion that agents view as a risk (and thus commands a premium) and an unpriced portion that is easily diversifiable (and thus does not command a premium). The priced portion is related to priced risks in the economy. The unpriced portion is specific to the measurement of the candidate factor, such as capturing the noisy estimation of true exposure, and is unrelated to returns or other risk factors[16]. Specifically:

$$\boldsymbol{g} = \boldsymbol{\eta}'\boldsymbol{\Omega} + \boldsymbol{\zeta}, \quad \mathrm{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) = 0, \tag{5}$$

where $\boldsymbol{g}$ is the potentially priced candidate physical climate risk factor and $\boldsymbol{\eta}$ is exposure to the same K priced risks in the economy as Eq. 4 - collected in the matrix $\boldsymbol{\Omega}$. The term $\boldsymbol{\zeta}$ is measurement error.

[15]For example, Pástor et al. (2022) show that a "green" factor that buys "green" stocks and sells "brown" stocks is correlated with a value factor that buys stocks with high book-to-market ratios (value stocks) and sells stocks with low book-to-market ratios (growth stocks). Lanfear et al. (2019) provide further evidence that momentum, size, and value factors are correlated with severe weather events. The estimated physical climate risk premium will consequently be biased if any of these factors are omitted from the asset-pricing model.

[16]Giglio and Xiu (2021) mainly focus on non-tradeable factors, such as consumption and liquidity, that are more prone to omitted variable bias since they are motivated by sparse, stylised theoretical models. Empirically, non-tradeable factors are also likely to be prone to measurement error since they utilise non-financial data. For example, by testing aggregate hurricane loss growth as a risk factor (Braun et al.; 2021). In this paper, I construct a tradeable risk factor that proxies for exposure to physical climate risk, which should lower measurement error compared to using a non-tradeable factor.

3.1.1 Omitted Factors

I now define the priced risks. Giglio and Xiu (2021) show that it is possible to "correctly recover the risk premium of any observable factor, even when not all true risk factors are observed and included in the model" (p.1949). The insight is that as long as the entire factor space can be recovered, the physical climate risk premium can be identified even when the other factors are unknown[17]. Thus, I can control for omitted factors. The priced portion in Eq. 5 is, by definition, the portion of the candidate factor that may have an associated risk premium, and I define it as $\widehat{\boldsymbol{g}} = \hat{\boldsymbol{\eta}}'\boldsymbol{\Omega}$. Estimating this portion is, however, a difficult task when one does not know all priced risks in the economy. Following Giglio and Xiu (2021), I thus obtain K latent factors that span the factor space via a principal component analysis on the returns of j test assets, where $j : [1, J]$, and collect them in the matrix $\boldsymbol{\Omega}$ that proxies for all priced risks in the economy. Further details of the approach are provided in the Appendix.

3.1.2 Measurement Error

I define unpriced risk, which is synonymous with measurement error, as $\widehat{\boldsymbol{\zeta}} = \boldsymbol{g} - \hat{\boldsymbol{\eta}}'\boldsymbol{\Omega}$ and assume it captures the difficulty in measuring physical climate risk. To aid interpretation, Giglio and Xiu (2021) suggest to view the unpriced portion as "measurement error that captures exposure to unpriced risk or idiosyncratic risk that is not fully diversified" (Giglio and Xiu; 2021, p.1955)[18]. Measurement error thus captures common variation across stocks "unaccompanied by a return premium" (Clarke; 2022, p.159). I only ignore the unpriced portion of the physical climate risk factor when the priced factors are uncorrelated with the unpriced portion of the factor (Daniel et al.; 2020): $\text{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) = 0$[19].

Suppose that physical climate risk does have a large unpriced component $\boldsymbol{\zeta}$. The unpriced component $\boldsymbol{\zeta}$ may indeed co-vary with priced sources of risk in the economy. To capture this idea, I depart from Giglio and Xiu (2021) and assume the true structure of priced risks can be written as:

$$\bar{\boldsymbol{\Omega}} = \boldsymbol{\Omega} + \boldsymbol{v}, \quad \text{Cov}(\bar{\boldsymbol{\Omega}}, \boldsymbol{v}) \neq 0, \quad \text{and}, \quad \text{Cov}(\boldsymbol{v}, \boldsymbol{\zeta}) \neq 0, \tag{6}$$

[17] Giglio and Xiu (2021) show that this is due to a general rotation invariance result. See also Giglio et al. (2022, p.7-11) for a review of these methods applied in an asset-pricing context.

[18] As long as the number of assets used to construct the physical climate risk factor is large, such as $N > 30$, then idiosyncratic risk is diversified away and can be assumed to equal zero. Otherwise, when the common variation is specific to some stocks, and when the agent is fully diversified, the unpriced portion is not priced as a systematic risk factor (Roll and Ross; 1984).

[19] In the Appendix, I provide reasons why physical climate risk measurement error may be correlated with priced factors.

where $\bar{\boldsymbol{\Omega}}$ are true priced risks, $\boldsymbol{\Omega}$ are the estimated priced risks in the economy (i.e., the latent factors), and $\boldsymbol{\upsilon}$ is the portion of priced risks that may be related to noise in the physical climate risk factor $\boldsymbol{\zeta}$. Substituting Eq. 6 into Eq. 5 and rearranging gives:

$$\boldsymbol{g} = \boldsymbol{\eta}'\bar{\boldsymbol{\Omega}} + (\boldsymbol{\zeta} - \eta\boldsymbol{\upsilon}), \tag{7}$$

where $\eta\boldsymbol{\upsilon}$ biases the estimated loading on $\bar{\boldsymbol{\Omega}}$ since $\text{Cov}(\bar{\boldsymbol{\Omega}}, \boldsymbol{\upsilon}) \neq 0$. This implies that if the true priced risks in the economy are associated with the physical climate risk measurement error then this measurement error should be explicitly controlled for. Furthermore, it provides evidence that some portion of physical climate risk is mispriced by agents since the unpriced portion co-varies with priced risks in the economy.

3.1.3 Risk Premia

Finally, given the issues of omitted factors and measurement error, I estimate each latent factor's risk premium and collect them in the vector $\hat{\boldsymbol{\lambda}}$, that denotes they are sample estimates[20]. The estimated risk premium in the three-pass procedure is given as:

$$\gamma = \hat{\boldsymbol{\eta}}'\hat{\boldsymbol{\lambda}}, \tag{8}$$

that says the risk premium γ of the potentially priced candidate physical climate risk factor $\boldsymbol{g}$ is the sum of the candidate factor's loading on each priced risk factor $\hat{\boldsymbol{\eta}}$ and their corresponding risk premium $\hat{\boldsymbol{\lambda}}$. The name of the three-pass procedure thus stems from the fact I first extract the principal components, then identify the risk premia of the estimated latent factors, then estimate the time-series regression in Eq. 5 (see Giglio and Xiu, 2021, p.1959).

[20] See the Appendix for details.

3.2 Measurement Error Tests

To test whether measurement error is related to priced risks, I estimate the following time-series regression:

$$\boldsymbol{\zeta} = d + \boldsymbol{\chi}'\boldsymbol{\Omega} + \boldsymbol{\epsilon}, \quad i.i.d.\ \boldsymbol{\epsilon} \sim \mathcal{N}(0,1), \tag{9}$$

where $\boldsymbol{\zeta}$ is a time-series vector containing measurement error in the physical climate risk factor $\boldsymbol{g}$, d is the intercept, $\boldsymbol{\chi}$ is a vector of estimated exposure to each priced factor in the matrix $\boldsymbol{\Omega}$, and $\boldsymbol{\epsilon}$ is a vector containing the error term. A significant association provides evidence that $\text{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) \neq 0$, the unpriced portion should not be ignored by agents, and the unpriced portion should be added to the asset-pricing model.

I depart from Daniel et al. (2020) who remain "agnostic as to what these unpriced sources of common variation in returns represent", by examining three candidate drivers of the un-priced common variation in physical climate risk exposure. These are empirically estimating in the following time-series regression:

$$\boldsymbol{\zeta} = h + \boldsymbol{\delta}'\boldsymbol{P} + \boldsymbol{\epsilon}, \quad i.i.d.\ \boldsymbol{\epsilon} \sim \mathcal{N}(0,1), \tag{10}$$

where $\boldsymbol{\zeta}$ is a vector containing measurement error in the physical climate risk factor $\boldsymbol{g}$, h is the intercept, $\boldsymbol{\delta}$ is a vector of the estimated loadings, $\boldsymbol{P}$ is a matrix of the candidate sources of common variation, and $\boldsymbol{\epsilon}$ is a vector containing the error term.

The first candidate source is the five common risk factors identified by Fama and French (2015). Since these are well-established priced risk factors, a significant association with measurement error provides reasonable evidence that innovations in the unpriced portion of the physical climate risk factors are driven by priced variation.

The second candidate source is industry portfolio returns. Even well-established factors, such as the value factor, have a priced and unpriced component that is driven by entire industries entering risk-factor-mimicking portfolios at the same time, thus driving returns in the candidate factor (Daniel et al.; 2020). This is especially plausible for physical climate risk since some industries are known to have higher material exposure

than others (Herz and Rogers; 2016; Addoum et al.; 2020; Bortolan et al.; 2022).

The third candidate source is realised severe weather events. There is growing evidence that agents appear to react to severe weather events with surprise, yet learn more about these disasters as their occurence increases over time (Pankratz et al.; 2022; Griffin et al.; 2022; Addoum et al.; 2021; Hong et al.; 2019). These events, and their severity, should therefore be able to explain errors in physical climate risk factors as agents update their understanding of exposure from the event. To improve the identification strategy, only severe weather events that are short-lived, such as hurricanes, floods, and severe storms, are assessed contemporaneously with errors and not long-lived events such as extreme temperatures. Consequently, the following model is estimated:

$$\boldsymbol{\zeta} = h + \boldsymbol{\delta}' \, log(\boldsymbol{P} + 1) + \boldsymbol{\epsilon}, \quad i.i.d. \ \boldsymbol{\epsilon} \sim \mathcal{N}(0, 1), \tag{11}$$

where $\boldsymbol{P}$ now contains damages from severe storms, tropical cyclones, and floods, and is logged because damages are skewed.

3.3 Sensitivities in the Empirical Strategy

Some sensitivities of the approach taken in this paper warrant further elaboration. First, the choice of test assets $\boldsymbol{R}$ is important because it is assumed the physical climate risk factor *spans* the test assets, thus an estimate of the risk premium can be obtained. A wide range of test assets that are known to span the cross-section of returns can consequently be used to partially mitigate this issue. However, the results obtained are still conditional on the set of test assets used, such that if $\boldsymbol{g}$ is weak I will conclude that it weakly prices the cross-section of returns. An alternative approach for future work could utilise supervised principal component analysis to identify test assets that are related to $\boldsymbol{g}$, as posited by Giglio, Xiu and Zhang (2021).

Second, a similar sensitivity exists with regards to the number of latent factors K that are assumed to exist in the data. To answer this, the first 15 eigenvalues of the covariance matrix of returns $\boldsymbol{R}$ is plotted to determine the number of latent factors K. I also assess the sensitivity of the conclusions to the number of latent factors chosen.

Third, the estimated standard errors are likely to suffer from auto-correlation and heteroskedasticity. I utilise Newey and West (1987) robust standard errors with a lag equal to $4(T/100)^a$, where T is the number of periods in the sample and $a = \frac{2}{9}$ (i.e., the Bartlett kernel) (Bali et al.; 2016).

4 Data

4.1 Physical Climate Risk Data

The measure of firm-level physical climate risk exposure used in this paper is provided by *Four-Twenty Seven*, a leading climate data-vendor acquired by Moody's Corporation in 2019. Firms' exposure is measured from 0 (low risk) to 100 (high risk) and assessed at the facility-level before a weighted-sum is calculated to create a firm-level score. The weights correspond to industry-specific vulnerabilities determined by *Four Twenty-Seven*.

Historical baselines are used to observe climate information at the location of a facility, before projecting the climate dynamics to a future period and assessing the level of impact the facility is likely to have on the firm if a severe weather event occurs. The use of *facility*-level information is an important improvement from existing approaches that rely on using a firm's headquarters as a proxy for their geographical exposure. These approaches suffer when firms' geographical exposure is diverse and spans many climatic zones, which is indeed likely for many publicly traded stocks.

The data is obtained in July 2018 for a large *cross-section* of over two-thousand traded stocks across the world. Each stock has one physical climate risk score per exposure type. I choose to subset the sample to ensure the physical climate risk score is a reasonable proxy for true exposure. First, only physical climate risk scores that use historical baselines before my sample period of January 2010 to December 2019 are kept in the dataset. This ensures agents could have collected the climate information at any point *during* the sample period, consequently incorporating the information into the price of a stock.

Second, physical climate risk scores are only kept in the dataset if a firms' time-varying geographical exposure is 90% similar to their exposure in 2018, thus reasonably being reflective of their physical climate risk exposure

at any point during the sample period. To achieve this, the *Four Twenty-Seven* scores are matched to the Compustat Segments database to calculate historical geographical exposure - resulting in 542 matches that are entirely US stocks. This database conveniently holds information on over 70% of North American stocks and labels geographical segments consistently over time with ID numbers. Since there exists no standardised method for disclosing segment information (firms can disclose a region (Asia) or a specific country (Thailand) when reporting the location of the same geographical segment), this is especially useful. Equipped with this information, the Jaccard Index for the ID numbers is calculated. This proxies for the similarity between a given year and 2018 (Fletcher et al.; 2018)[21]. After assessing the average geographical similarity to 2018, the sample period is then limited to January 2010 to December 2019, where the average similarity to 2018 is still high (over 90%).

4.2 Four Measures of Physical Climate Risk

Four physical climate risk measures from *Four Twenty-Seven* pass the thresholds posited in the previous section and constitute the main risks assessed in this paper. These measures are all considered "operational" risks since they impact the ability of a firm to continue its day-to-day operations.

First, exposure to sea-level rise is determined by global high resolution digital elevation models for a stock's known facilities and is linked to local storm surge and sea-level rise estimates between 2017 and 2040 under RCP8.5 (an extreme socio-economic pathway).

Second, exposure to hurricanes is measured by relating facilities to the cumulative wind velocity over the period 1980-2016 of the nearby field radii of minimal tropical storm, strong tropical storm, hurricane, and major hurricane force winds.

Third, heat stress is measured as the expected increase in electricity costs due to rising temperatures holding inflation and technology constant, the relative expected change in annual maximum temperatures, and the expected number of additional hot days in a year that exceed the 90th percentile of the baseline period (1975-2005). These factors are projected to 2020-2040 and capture the expected productivity losses from

[21] The approach is detailed more fully in the Appendix.

workers, energy systems, and equipment during historically severe events.

Fourth, extreme rainfall measures the change in rainfall volumes, intensity, and additional wet days that exceed the local 95th percentile for each facility using similar baseline and projection periods to heat stress.

4.3 Financial Data

Financial data from January 2010 to December 2019 for stocks with physical climate risk scores are used to construct the physical climate risk factors. Monthly returns, shares outstanding, and monthly closing prices are first collected from the Center for Research in Security Prices (CRSP). Following Jensen et al. (2021), micro-cap stocks (market equity < NYSE 20th percentile) and penny stocks (monthly closing price < \$5) are dropped at eacth time t[22]. These choices follow a large literature on the effect of small-cap stocks on asset-pricing anomalies and the difficulty in trading them (Fama and French; 2008; Hou et al.; 2020)[23].

The monthly risk-free rate, NYSE market equity breakpoints, and monthly returns for the market, size, value, investment, and profitability risk factors are obtained from Ken. French's Data Library. Additionally, 32 value-weighted portfolios sorted on size, book-to-market, and investment from the same source are collected and are used as the test assets $\boldsymbol{R}$. Ten value-weighted industry portfolios are also collected. These are Consumer Non-Durables, Consumer Durables, Manufacturing, Energy, High Technology, Telecommunications, Shopping, Healthcare, Utilities, and Other[24].

To construct the cross-sectional market factor, rolling 6-month regressions of stock-level monthly excess returns on the market portfolio are estimated to obtain stock-level CAPM betas. The market portfolio is defined as the excess return on a value-weighted portfolio of all firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ stock exchanges. The de-meaned CAPM betas are then used at each month to estimate the returns to the market factor (see Eq. 3).

[22] Winsorizing market equity at the NYSE 80th percentile, as in Jensen et al. (2021), is less important in this paper since value-weighted portfolios are not constructed.

[23] In similar studies, Pástor et al. (2022) do not drop any stocks when constructing a green-minus-brown factor with a sample that also includes many small stocks, whilst Lioui and Tarelli (2022) drop stocks with market equity < NYSE 30th percentile and a closing price < \$1.

[24] I thank Ken. French for making this data available on his website:
https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

For expected returns, not *realised* returns, I utilise a measure proposed by Martin and Wagner (2019) that uses options prices to proxy for the expected return on a stock. An important contribution of their derived formula is that it only utilises forward-looking information from real-time options prices. I follow the construction of this measure in a similar paper by Acharya et al. (2022, p.16-17). That is, use OptionMetrics IvyDB US to obtain implied volatility surfaces (put and call prices) and stock prices for the stocks in the sample. The Treasury zero coupon yield is used as the risk-free rate and the most recent dividend is used as the ongoing dividend yield for each stock[25]. I then denote $E_t(R_{j,t+1})$ as the annualised expected excess return for stock j in month t to month t_{+1}.

Table 1 reports summary statistics for the financial data. The mean monthly excess return over the sample period for firms with physical climate risk scores is 1.33%. The largest monthly decline is 53.39% whilst the largest gain is 81.51%. The smallest stock in the sample has a market equity of $440 million and the largest $1.2 trillion. The risk-free rate is close to zero over the sample period.

4.4 Other Data

To assess when severe weather events occur, CPI-adjusted billion dollar damages are collected from the National Oceanic & Atmospheric Administration (NOAA; 2022)[26]. Damages include total losses (insured and uninsured) from physical damage to residential, commercial and government buildings, material assets in buildings, the time-cost for businesses, vehicles, public and private infrastructure, and agricultural assets (Smith and Katz; 2013). Damages to natural capital, healthcare-losses, and the value of loss of life are not included. The time-series of the billion dollar damages controls for inflation but does not consider other known factors that have caused an increase in the damages caused by severe weather, such as population growth and the increased value of exposed assets (Barthel and Neumayer; 2012; Pielke Jr et al.; 2008).

US CPI-adjusted billion dollar disaster events are also collected from NOAA[27]. This data includes the estimated damages from each event as well as a short description about the nature of the disaster. Disasters

[25] I sincerely thank Acharya et al. (2022) for sharing their data. See Acharya et al. (2022) and Martin and Wagner (2019) for a thorough explanation of the measure.
[26] Available at https://www.ncdc.noaa.gov/billions/time-series.
[27] Available at https://www.ncdc.noaa.gov/billions/events/US/2010-2019.

with less than 30 events are dropped. The remaining disasters are severe storms, tropical cyclones, and flooding. Damages are logged because they are skewed, such that damages = log(damages + 1). For periods where no CPI-adjusted billion dollar disaster event occurs, damages equal zero.

5 Results

This section provides the results for the estimation of physical climate risk premia. I choose to compare the physical climate risk factors with five common risk factors identified by Fama and French (2015) as a benchmark (i.e., the market, size, value, profitability, and investment factors). Table 2 reports the average performance of the four physical climate risk factors. The *SEA* and *WIND* factors have positive average monthly realised excess returns of 0.70% and 0.06%, respectively. The *HEAT* and *RAIN* factors have negative average monthly realised excess returns of -1.16% and -0.78%, respectively. The correlation between the physical climate risk factors does not exceed 55% (Table 3). The magnitude of these monthly excess returns is also comparable to other known risk factors, such as the value factor (-0.20%) and the profitability factor (0.12%). The market factor has an average monthly realised excess return of 1.12% across the sample period. Figure 1 shows the cumulative raw excess return of the physical climate risk factors. The *SEA* and *WIND* factors return 83.84% and 6.70%, respectively. The *HEAT* and *RAIN* factors return -138.01% and -93.23%, respectively.

Table 4 shows the result of regressing each physical climate risk factor on a cross-sectional market factor. The *HEAT* and *RAIN* factors load significantly on the market factor yet also have significant CAPM alphas, implying they may be additional priced risk factors. The *SEA* and *WIND* factors do not load significantly on the market factor and also have insignificant CAPM alphas (although the *SEA* factor's alpha is significant at the 10% level). This would imply these factors are pure noise and I test this next by estimating risk premia whilst controlling for measurement error (noise).

5.1 Realised Risk Premia

Table 5 report the main results following the three-pass procedure of Giglio and Xiu (2021). Column 2 reports the average monthly realised excess return of each physical climate risk factor as a benchmark result.

Columns 3-9 then provide the estimated risk premium for a unit exposure (i.e., a beta of 1 to physical climate risk and 0 to all other risks) to each physical climate risk factor under different choices of the number of latent factors present in the data. The sign of each estimated premium is consistent across each choice of latent factors. Of particular importance is Column 9, which reports the estimated risk premia with the maximum number of latent factors assessed in this paper (7) - results are consistent when $K \geq 3$. The results show that the *WIND* and *HEAT* factors have statistically significant risk premiums of 0.39% and -0.59%, respectively. The *SEA* and *RAIN* factors have statistically insignificant premiums of 0.33% and 0.24% respectively. As a comparison, the estimated risk premia for the market, size, and value factors are 1.12%, -0.01%, and -0.28%, respectively (see Table 13 in the Appendix). The risk premia estimates for these latter factors are very similar to their risk-factor-mimicking portfolios, which is to be expected for factors that are priced (see Table 2). Conversely, the risk premia estimates for the physical climate risk factors are notably different from their risk-factor-mimicking portfolios (to see this, compare Column 2 to Column 9 in Table 5). The main result is that the three-pass procedure identifies significant risk premiums for exposure to hurricane risk, *WIND*, and heat stress, *HEAT*. There is no significant premium for exposure to sea-level rise, *SEA*, or extreme rainfall, *RAIN*.

As a robustness check, I also estimate risk premia following the two-pass Fama and MacBeth (1973) procedure (Appendix, Table 12) and see, again, that the *WIND* factor commands a significantly positive risk premium whilst the *HEAT* factor commands a significantly negative risk premium. In the two-pass procedure, the *SEA* factor is associated with a significant positive price of risk, whereas in the three-pass procedure the result is not statistically significant.

5.2 Expected Risk Premia

Realised stock returns can lead to poor estimates of risk premia if the chosen sample period suffers from multiple information shocks (Elton; 1999)[28]. To test this, I now utilise the expected return measure of Martin and Wagner (2019) to estimate physical climate risk premia.

Table 6 shows the result of regressing the monthly annualised *expected* excess return of each stock on a year-by-physical climate risk raw score interaction term. Like Acharya et al. (2022), who utilise *Four Twenty-Seven* data and the same expected return proxy, I estimate a significantly positive expected return for heat stress only after 2014. I also similarly estimate a negative coefficient for exposure to hurricanes/tropical cyclones but identify a statistically significant association[29]. There is a significantly negative association across most years between expected returns and exposure to sea-level rise and a mixed association between expected returns and extreme rainfall. In sum, these results appear to run counter to the realised risk premia estimates in Section 5.1. However, notice that those tests focus on a long-short portfolio that isolates a candidate physical climate risk factor, whereas the panel tests in Table 6 focus on the *level* of physical climate risk exposure.

My attention consequently turns to the so-called "greenium" which, for ease of interpretation for my setting, I call the "exposure spread" - the expected return difference between highly exposed stocks and less exposed (safe) stocks[30]. Figure 2 and Figure 3 plot the time-series *expected* return of physical climate risk-weighted portfolios for exposure to hurricanes/tropical cyclones and heat stress, respectively. The main result is that the mean exposure spread in expected returns is positive for hurricane risk which is the same result as in Section 5.1 using realised returns. The mean exposure spread in expected returns is negative for heat stress but close to zero, which is different than the realised return result (that exposure to heat-stress has a negative premium). This implies that agents *expect* no difference between heat stress exposed and safe stocks, yet realised a difference. For both risks, unlike the green factor in Pástor et al. (2022, Section 5.1), the sign of the exposure spread between exposed and safe stocks is not consistent over the sample and the mean spread

[28]For realised returns, r_t, to be a good proxy of expected returns, $E_{t-1}(r_t)$, information shocks, ϵ_t, should have a mean of zero across the sample: $r_t = E_{t-1}(r_t) + \epsilon_t$. Pástor et al. (2022) and Sautner et al. (2022) document how, due to rising attention, climate-related shocks may in fact not have mean zero between 2010 and 2019.

[29]This may be driven by my smaller sample that controls for geographical exposure over time. My results remain the same when I normalise the scores, as in Acharya et al. (2022).

[30]To be clear, so-called safe stocks are only *relatively* safe compared to highly exposed stocks in the sample owing to a potential selection bias from *Four Twenty-Seven* when they choose which stocks to assess.

is small.

5.3 Pricing Physical Climate Risk

How much of the *realised* risk factor performance is priced? The variation of each physical climate risk factor that can be explained by priced latent factors is reported in Table 7. Rows 2-6 show the R^2 for the Fama and French (2015) five-factors - my benchmark factors. Understandably, almost all variation in the market, size, and value factors is priced. This is a similar result to Giglio and Xiu (2021). Rows 7-10 then show the R^2 for the physical climate risk factors. Only 31% of the *SEA* factor, 8% of the *WIND* factor, 38% of the *HEAT* factor, and 17% of the *RAIN* factor can be explained by the 7 latent factors[31]. Figure 4 plots the priced portion of each factor alongside its realised factor performance to show this result. The Fama and French (2015) factors are well-priced, shown by priced and realised factor innovations that are very close to one another, whereas the physical climate risk factors show large deviations between their priced and realised performance. Figure 5 shows the cumulative effect of this result by plotting the cumulative return of each physical climate risk factor with and without measurement error (i.e., the realised portion versus only the priced portion)[32].

The standard approach in the asset-pricing literature views these pricing errors as noise (classical measurement error). My attention now turns to testing this empirically. The errors can be viewed as errors made by agents if they are correlated with priced latent factors (Daniel et al.; 2020). Table 8 shows the result of regressing the error from each physical climate risk factor on the priced latent factors. The results show that measurement error is significantly associated with many latent factors, thus $\text{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) \neq 0$, and there exists some unpriced source of common variation that can explain the measurement error in pricing physical climate risk. Errors in the profitability factor (RMW) are the only errors from the Fama and French (2015) five-factors that are significantly associated with many priced latent factors (see Table 14 in the Appendix), thus confirming that this result is predominantly unique to the physical climate risk factors. Consequently, I provide indicative evidence that measurement error in the physical climate risk factors can be thought of as mispricing rather than being driven purely by noise.

[31] Figure 7 in the Appendix visualises the R^2 values.

[32] Figure 8 in the Appendix plots the difference between the realised factor performance and the priced factor performance (i.e., the measurement error ζ).

The sources of the unpriced common variation in the physical climate risk factors are then identified. The mechanism behind this phenomenon is relatively straightforward: priced factors may enter the physical climate risk-factor-mimicking portfolios and co-vary with the factor, confounding the priced and unpriced portions of physical climate risk. This is particularly material for agents since it affects their utility through their (unwilling) exposure to priced risks. Table 9 shows the result of regressing the errors in each physical climate risk factor on the Fama and French (2015) five-factors. The results show that the market factor and the value factor load significantly on all four physical climate risk errors. The profitability factor (RMW) can explain the *SEA*, *HEAT*, and *RAIN* factor errors, whilst the investment factor (CMA) can explain the *SEA*, *WIND*, and *RAIN* factor errors.

Table 10 then shows the result of regressing the errors in each physical climate risk factor on industry factors. It is clear from the results that industry has an heterogeneous effect on measurement error: Manufacturing and Energy returns can both explain errors in the *WIND* factor but not any other physical climate risk, Telecommunication returns can explain errors in all physical climate risks *except* the *WIND* factor, Shopping returns can explain errors in the *SEA* and *WIND* factors, Healthcare returns can explain errors in the *SEA*, *HEAT*, and *RAIN* factors, and Utility returns can explain errors in the *SEA* and *RAIN* factors. High Technology returns can explain errors in all physical climate risks.

Table 11 then regresses the errors in each physical climate risk factor on *realised* extreme damages from severe storms and tropical cyclones. A significant association provides evidence that agents did not anticipate exposure, yet, when the event unfolds, react by learning from the disaster about true exposure. Panel A in Table 11 shows that a 1% increase in damages from severe storms is associated with a decrease in the errors of the *WIND* and *RAIN* factors of -0.08% and -0.11%, respectively. Similarly, Panel B in Table 11 shows that a 1% increase in damages from severe storms *and* tropical cyclones is associated with a decrease in the errors of the *WIND* factor of -0.08%[33]. In sum, there is preliminary evidence that common risk factor returns, industry returns, and realised severe weather events are all sources of unpriced common variation

[33]Tropical cyclones are not assessed alone because there are only 12 events and consequently many zeroes. Both severe storms and tropical cyclones increase the chance of wind damage, hence their positive loading on the *WIND* factor and not the *RAIN* factor (which captures exposure to extreme rainfall and is represented better in Panel A with only severe storms as the explanatory variable) is plausible.

in physical climate risk factor innovations.

6 Explaining the Heat Stress Discount

Before concluding, I provide remarks on why the premium associated with exposure to heat stress may be negative. Heat stress is measured as the expected increase in electricity costs due to rising temperatures holding inflation and technology constant, the relative expected change in annual maximum temperatures, and the expected number of additional hot days in a year that exceed the 90th percentile of the baseline period (1975-2005). These variables are projected to 2020-2040 and capture the expected productivity losses from workers, energy systems, and equipment during historically severe events. I first repeat the results found in this paper. The risk premium for a unit exposure to heat stress is negative when using realised returns and controlling for omitted factors and measurement error, and negative but close to zero when using expected returns constructed from options (Martin and Wagner; 2019). This runs counter to the theoretical approach of Pástor et al. (2021) that motivated my approach and predicts a positive risk premium for exposure to (physical) climate risk[34]. There are two arguments for why a unit exposure to heat stress may command a negative price of risk.

The first argument is that *unexpected* shocks to agents' preferences occurred over the sample period. This would cause the realised performance of the heat stress factor to be negative if agents internalise negative information about heat stress. Indeed, Figure 3 shows a negative exposure spread prior to 2015 and again between 2017-2019. Pástor et al. (2022) provide evidence for such an argument by showing that unexpected attention to climate change (in a general sense) can artificially lower the returns of brown stocks (in my case brown stocks are exposed stocks). To explore whether this is indeed the case, I follow Pástor et al. (2022, Section 5.2) and exploit unexpected extreme temperature news in the US that is correlated with realised returns but has an expectation of zero. I de-mean the monthly extreme temperature news-series from Ardia et al. (2022) between February 2010 and June 2018 and denote its contemporaneous time-series innovations

[34]This approach is akin to the "disaster view" of climate risk (Giglio, Maggiori, Rao, Stroebel and Weber; 2021, p.3534). When uncertainty is predominantly based on the climate system as opposed to the net zero transition path, agents demand compensation for holding assets that co-vary with bad climate times since these assets provide no hedge against the bad state of nature.

as $\boldsymbol{x}$ and its lagged innovations as $\boldsymbol{x_{t-1}}$[35]. Then, I estimate the following regression:

$$\boldsymbol{g}_{HEAT} = \alpha + \beta_x \boldsymbol{x} + \beta_{x_{t-1}} \boldsymbol{x_{t-1}} + \boldsymbol{\epsilon}, \quad i.i.d.\ \boldsymbol{\epsilon} \sim \mathcal{N}(0,1), \tag{12}$$

where $\boldsymbol{g}_{HEAT}$ is the heat stress risk factor, $\boldsymbol{x}$ is unexpected extreme temperature news, $\boldsymbol{x_{t-1}}$ is the lagged unexpected extreme temperature news, and $\boldsymbol{\epsilon}$ the usual error term. The estimate $\widehat{\alpha}$ = $\bar{\boldsymbol{g}}_{HEAT}$ - $\widehat{\beta}_x \bar{\boldsymbol{x}}$ - $\widehat{\beta}_{x_{t-1}} \bar{\boldsymbol{x}}_{t-1}$ then provides the sample return of the heat stress factor after controlling for unexpected extreme temperature news, where $\bar{\boldsymbol{g}}_{HEAT}$, $\bar{\boldsymbol{x}}$, and $\bar{\boldsymbol{x}}_{t-1}$ denote sample means. Note, the sample mean return is usually a good measure of risk premia. I find that $\widehat{\alpha}$ equals -1.20 (with robust t-statistic = -2.46), therefore providing preliminary evidence that unexpected attention cannot reverse the negative premium to heat stress.

The second argument is that there exists potential mispricing of climate risks. Empirical evidence has been provided, among others, by Acharya et al. (2022), Griffin et al. (2022), Bortolan et al. (2022), Pankratz et al. (2022), Choi et al. (2020), and Hong et al. (2019) that all identify asset pricing impacts related to extreme temperatures. Alongside this evidence, the expected return exposure spread in Figure 3 indicates that agents do not expect any difference between exposed and safe stocks, on average, over the sample. However, the negative *realised* performance of the heat stress factor suggests agents then learn about exposure after events. Since the empirical strategy employed in this paper seeks to control for omitted factors, it is also difficult to explain such mispricing as being caused by heat stress exposure being related to other risk factors. Indeed, one potential cause of mispricing that conforms to the results in this study is the difficulty in translating physical climate risk exposure into actionable information[36].

[35]The news index is based on the corpus of 10 newspapers and 2 newswires. Available at: https://sentometrics-research.com. Whilst daily data may be preferred for severe weather event shocks, heat stress occurs over a pro-longed period of time (e.g, heatwaves and droughts over weeks/months) that means a monthly measure is likely still suitable.

[36]As motivated at the beginning of this paper, Krueger et al. (2020) survey institutional investors and find they believe climate risks are under-priced. Pinchot et al. (2021) also document that it is "unlikely publicly available guidance fully equips companies and financial organizations to assess the range of potential physical climate hazards documented by climate science" (p.2).

7 Conclusion

Despite the imperative for physical climate risk to be priced, it is unclear if such a risk is deemed a systematic risk factor by agents. To answer this, I construct physical climate risk factor-mimicking portfolios from risk scores that aggregate exposure to sea-level rise, hurricane risk, heat stress, and extreme rainfall for each of a firm's facilities. Risk premiums associated with a unit exposure to each of these risks is then estimated for the US equity market and explicit attention is given to whether measurement error is due to noise or mispricing.

I provide indicative evidence that exposure to hurricane risk commands a positive risk premium and exposure to heat stress commands a negative risk premium for the choice of test assets used in this paper. This result also holds when using expected returns for hurricane risk, whilst heat stress expected returns have the same sign to the realised return estimates but are much closer to zero. Both exposure to sea-level rise and exposure to extreme rainfall are not priced as systematic risk factors.

An important novelty is viewing, under certain conditions, measurement error not as an error by the researcher (classical measurement error), but by agents when pricing physical climate risk (non-classical measurement error). With this interpretation, I provide evidence that physical climate risk is priced with error compared to other known risk factors such as market risk. Measurement error in the physical climate risk factors are significantly associated with *priced* latent factors, motivating the idea that some portion of the physical climate risk factors are mispriced by agents rather than being pure noise. Supporting this argument, I find that agents do not *expect* any difference between heat stress exposed stocks and safer stocks but then learn about different levels of exposure after severe events (evidenced by a negative realised risk premium). Conversely, agents expect to receive compensation for exposure to hurricane risk - and consequently do so over my sample period. The Fama and French (2015) five-factors, industry portfolio returns, and realised severe weather events all significantly explain the pricing errors. This provides evidence that the unpriced sources of common variation are material for agents, yet it is ignored for some particular reason. Aside from the fact that physical climate risk is difficult to measure, this poses an interesting puzzle - especially given that severe weather events are not necessarily a recent phenomenon for agents to understand.

Further research could utilise my approach to measurement error, since it provides one approach to disentangle the signal-to-noise ratio of physical climate risk[37]. Another avenue for further research is to explore the value of *realised* physical climate risk events since they provide useful information to agents about exposure. Since these events are rare, novel sources of data may be required to obtain enough information to understand historical exposure to physical climate risk.

[37]see Berg et al. (2021) and Giglio and Xiu (2021) for alternative approaches and Yoon and Serafeim (2022) and King and Berchicci (2022) for a useful discussion on issues with ESG measurement.

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Tables

Table 1: Summary statistics: financial data. I provide monthly summary statistics for the 479 unique US stocks that are used to construct the physical climate risk factors. The sample period is from January 2010 to December 2019. Micro-cap stocks (market equity < NYSE 20th percentile) and penny stocks (monthly closing price < $5) are dropped. Excess returns and the risk-free rate are in percent per month. Market equity is in billions $USD. SD is the standard deviation.

Variable	*N*	mean	median	SD	min	max
Excess return	479	1.33	1.31	8.06	-53.39	81.51
Market equity	479	29.94	13.22	52.39	0.44	1200.25
Risk-free rate	1	0.04	0.01	0.07	0.00	0.21

Note: *N* gives the number of units (i.e, 479 firms).

Table 2: Summary statistics: factor performance. I provide monthly summary statistics in percent per month for the four physical climate risk factors constructed using climate exposure scores from *Four Twenty-Seven* and the Fama and French (2015) five factors for the US equity market. The sample period is from January 2010 to December 2019. Sea proxies for exposure to sea-level rise. Wind proxies for exposure to hurricanes/tropical cyclones. Heat proxies for exposure to heat stress. Rain proxies for exposure to extreme rainfall. MKT-RF is the excess market return. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor. SD is the standard deviation and Sharpe is the Sharpe Ratio.

Factor	*obs*	mean	t-stat	median	min	max	SD	Sharpe
Sea	119	0.70	1.61	0.96	-14.38	10.81	4.78	0.15
Wind	119	0.06	0.14	0.47	-14.37	9.87	4.47	0.01
Heat	119	-1.16	-2.69	-1.08	-13.57	13.01	4.71	-0.25
Rain	119	-0.78	-2.10	-0.05	-16.67	6.82	4.07	-0.19
MKT-RF	119	1.12	3.30	1.36	-9.55	11.35	3.74	0.30
SMB	119	-0.04	-0.17	0.20	-4.51	6.80	2.31	-0.02
HML	119	-0.20	-0.96	-0.41	-4.85	8.22	2.29	-0.09
RMW	119	0.12	0.89	0.13	-3.93	3.53	1.50	0.08
CMA	119	0.02	0.13	-0.02	-3.35	3.78	1.45	0.01

Table 3: Correlation matrix. I provide the correlation between the four physical climate risk factors constructed using climate exposure scores from *Four Twenty-Seven*. *SEA* proxies for exposure to sea-level rise. *WIND* proxies for exposure to hurricanes/tropical cyclones. *HEAT* proxies for exposure to heat stress. *RAIN* proxies for exposure to extreme rainfall.

	SEA	*WIND*	*HEAT*	*RAIN*
SEA	1.00	0.19	-0.54	-0.36
WIND	0.19	1.00	0.06	0.36
HEAT	-0.54	0.06	1.00	0.45
RAIN	-0.36	0.36	0.45	1.00

Table 4: CAPM regressions. I estimate separate monthly time-series regressions of realised physical climate risk factor performance on a market factor. The sample period is from March 2011 to December 2019. In order to place all factors on an equal footing, both the physical climate risk factors and the market factor are constructed following the cross-sectional approach adopted in Fama and French (2020) and Lioui and Tarelli (2022). SEA proxies for exposure to sea-level rise. $WIND$ proxies for exposure to hurricane/tropical cyclones. $HEAT$ proxies for exposure to heat stress. $RAIN$ proxies for exposure to extreme rainfall. MKT proxies for exposure to a market factor. For the market factor, I regress a vector of excess returns on a vector of lagged 12-month estimated rolling market betas at each period (see Eq. 3). The market betas are estimated via rolling 12-month regressions of excess stock returns on the excess market return.

	SEA	*WIND*	*HEAT*	*RAIN*
Alpha	0.81	0.07	-0.92	-0.92
	(1.90)	(0.24)	(-2.03)	(-2.43)
MKT	-0.28	-0.33	-0.84	0.71
	(-0.62)	(-0.97)	(-2.66)	(3.43)
R^2	0.01	0.01	0.06	0.06

Note: Robust t-statistics in parentheses.

Table 5: Giglio and Xiu (2021) three-pass regressions for the physical climate risk factors. I estimate monthly physical climate risk premia in percent per month for a unit exposure to physical climate risk following the three-pass procedure of Giglio and Xiu (2021) that controls for omitted factors and removes measurement error. The sample period is from January 2010 to December 2019. Sea proxies for exposure to sea-level rise. Wind proxies for exposure to hurricanes/tropical cyclones. Heat proxies for exposure to heat stress. Rain proxies for exposure to extreme rainfall. $\bar{\boldsymbol{g}}$ is the mean raw excess return for each factor. γ is the estimated risk premium using K latent priced factors and equals $\hat{\boldsymbol{\eta}}'\hat{\boldsymbol{\lambda}}$; where $\hat{\boldsymbol{\eta}}$ is a vector of factor loadings on each fundamental risk factor and $\hat{\boldsymbol{\lambda}}$ is a vector containing each fundamental risk factor's risk premium.

	Risk Premia Using K Latent Factors							
	$\bar{\boldsymbol{g}}$	$\gamma^{K=1}$	$\gamma^{K=2}$	$\gamma^{K=3}$	$\gamma^{K=4}$	$\gamma^{K=5}$	$\gamma^{K=6}$	$\gamma^{K=7}$
Sea	0.70	0.00	0.42	0.45	0.35	0.35	0.32	0.33
	(1.61)	(0.16)	(3.16)	(1.90)	(1.41)	(1.38)	(1.32)	(1.31)
Wind	0.06	0.05	0.16	0.16	0.40	0.41	0.39	0.39
	(0.14)	(1.45)	(2.23)	(2.11)	(2.44)	(2.32)	(2.16)	(2.32)
Heat	-1.16	-0.34	-0.75	-0.78	-0.66	-0.64	-0.59	-0.59
	(-2.69)	(-2.91)	(-4.79)	(-3.78)	(-2.85)	(-2.74)	(-2.27)	(-2.30)
Rain	-0.78	0.15	0.15	0.13	0.20	0.22	0.25	0.24
	(-2.10)	(2.87)	(1.94)	(1.03)	(1.24)	(1.32)	(1.59)	(1.66)

Note: Robust t-statistics in parentheses.

Table 6: Conditional expected returns and physical climate risk. I estimate separate panel regressions of monthly annualised expected excess stocks returns on a year-by-physical climate risk raw score interaction term, following Acharya et al. (2022). Controls include stock fixed-effects, month fixed-effects, and each stock's loading on the Fama and French (2015) five-factors plus momentum (estimated using the previous 24 months of data with a minimum of 6 months of prior data required). Standard errors are clustered at the year-month-stock level. $E_t(r_{j,t+1})$ is the monthly annualised expected excess stock return for stock j in percent per month using the options-data measure by Martin and Wagner (2019). Score$\times$ Y_{year} is the interaction term of interest. Sea is the raw proxy for exposure to sea-level rise. Wind is the raw proxy for exposure to hurricanes/tropical cyclones. Heat is the raw proxy for exposure to heat stress. Rain is the raw proxy for exposure to extreme rainfall. All proxies are exposure scores provided by *Four Twenty-Seven*. The scores are *not* de-meaned or normalised.

	Sea	Wind	Heat	Rain
		$E_t(r_{j,t+1})$		
Score$\times Y_{2011}$	-0.00	-0.01	-0.01	-0.02
	(-0.31)	(-0.40)	(-0.79)	(-0.93)
Score$\times Y_{2012}$	-0.05	-0.06	-0.02	-0.01
	(-4.29)	(-3.66)	(-1.65)	(-0.89)
Score$\times Y_{2013}$	-0.08	-0.08	0.00	-0.00
	(-7.67)	(-4.45)	(0.09)	(-0.23)
Score$\times Y_{2014}$	-0.07	-0.09	0.01	-0.01
	(-5.79)	(-5.40)	(0.82)	(-0.54)
Score$\times Y_{2015}$	-0.11	-0.09	0.08	0.04
	(-9.22)	(-5.26)	(5.92)	(2.84)
Score$\times Y_{2016}$	-0.12	-0.08	0.08	0.03
	(-9.56)	(-3.98)	(5.52)	(1.91)
Score$\times Y_{2017}$	-0.09	-0.08	0.02	0.01
	(-8.06)	(-4.41)	(1.42)	(1.21)
Score$\times Y_{2018}$	-0.09	-0.06	0.02	0.03
	(-7.32)	(-2.43)	(1.59)	(2.31)
Score$\times Y_{2019}$	-0.13	-0.12	0.09	0.37
	(-10.82)	(-4.06)	(4.44)	(1.64)
Controls	Y	Y	Y	Y
R^2	0.56	0.56	0.56	0.55

Note: Robust t-statistics in parentheses.

Table 7: Variation of the observed factor explained by latent factors. I estimate separate monthly time-series regressions of each candidate risk factor on K priced latent factors. The sample period is from January 2010 to December 2019. The R^2 from each regression proxies for the variation in the candidate risk factor that is priced. MKT-RF is the excess market return. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor. These initial five factors provide a benchmark that I compare the physical climate risk factors to. SEA proxies for exposure to sea-level rise. WIND proxies for exposure to hurricanes/tropical cyclones. HEAT proxies for exposure to heat stress. RAIN proxies for exposure to extreme rainfall.

Variable	$R^2_{K=1}$	$R^2_{K=2}$	$R^2_{K=3}$	$R^2_{K=4}$	$R^2_{K=5}$	$R^2_{K=6}$	$R^2_{K=7}$
MKT-RF	0.92	0.99	1.00	1.00	1.00	1.00	1.00
SMB	0.39	0.81	0.97	0.99	0.99	0.99	0.99
HML	0.08	0.37	0.93	0.93	0.96	0.97	0.97
RMW	0.16	0.19	0.24	0.29	0.31	0.50	0.51
CMA	0.00	0.18	0.55	0.67	0.84	0.88	0.88
SEA	0.00	0.09	0.27	0.28	0.28	0.29	0.31
WIND	0.00	0.01	0.01	0.07	0.07	0.08	0.08
HEAT	0.10	0.19	0.29	0.31	0.31	0.37	0.38
RAIN	0.03	0.03	0.14	0.14	0.15	0.17	0.17

Table 8: Relationship between physical climate risk measurement error and priced latent factors. I estimate separate monthly time-series regressions of the unpriced portion of each physical climate risk factor ζ on K priced latent factors, where κ: [1:K]. This tests explicitly whether measurement error ζ in the physical climate risk factors is related to priced latent factors K. The sample period is from January 2010 to December 2019. Sea proxies for exposure to sea-level rise. Wind proxies for exposure to hurricanes/tropical cyclones. Heat proxies for exposure to heat stress. Rain proxies for exposure to extreme rainfall.

Latent factors	Sea (ζ_{SEA})	Wind (ζ_{WIND})	Heat (ζ_{HEAT})	Rain (ζ_{RAIN})
Alpha	-0.22	-0.00	0.41	0.13
	(-1.96)	(-0.23)	(3.45)	(2.51)
κ_1	-0.01	-0.19	0.90	-0.54
	(-0.08)	(-6.33)	(6.43)	(-7.71)
κ_2	1.01	0.36	-0.90	0.00
	(7.21)	(12.00)	(-6.43)	(0.00)
κ_3	-1.38	0.07	0.93	1.13
	(-8.12)	(2.33)	(7.15)	(18.83)
κ_4	0.31	-0.99	-0.33	-0.27
	(2.38)	(-33.00)	(-2.20)	(-3.38)
κ_5	0.03	-0.11	-0.19	-0.30
	(0.21)	(-3.67)	(-1.12)	(-3.75)
κ_6	0.35	0.34	-0.69	-0.43
	(3.18)	(11.33)	(-5.31)	(-8.60)
κ_7	-0.46	-0.28	0.31	0.06
	(-4.65)	(-6.89)	(2.55)	(1.19)
R^2	0.67	0.91	0.60	0.82

Note: Robust t-statistics in parentheses.

Table 9: Relationship between physical climate risk measurement error and the Fama and French (2015) five factors. I estimate separate monthly time-series regressions of the unpriced portion of each physical climate risk factor ζ on the Fama and French (2015) five-factors. The sample period is from January 2010 to December 2019. Sea proxies for exposure to sea-level rise. Wind proxies for exposure to hurricanes/tropical cyclones. Heat proxies for exposure to heat stress. Rain proxies for exposure to extreme rainfall. MKT-RF is the excess market return. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor.

Factor	Sea (ζ_{SEA})	Wind (ζ_{WIND})	Heat (ζ_{HEAT})	Rain (ζ_{RAIN})
Alpha	-0.40	-0.21	0.75	-0.11
	(-3.06)	(-1.91)	(4.97)	(-1.35)
MKT-RF	0.09	0.12	-0.27	0.21
	(2.22)	(4.08)	(-5.62)	(10.71)
SMB	-0.05	-0.07	0.09	-0.17
	(-0.74)	(-1.14)	(1.35)	(-3.47)
HML	-0.59	-0.27	0.40	0.28
	(-6.56)	(-5.35)	(5.07)	(5.56)
RMW	-0.27	0.01	0.55	0.29
	(-2.76)	(0.20)	(5.60)	(4.88)
CMA	-0.28	0.53	0.15	0.32
	(-2.39)	(6.60)	(1.51)	(4.67)
R^2	0.55	0.28	0.52	0.66

Note: Robust t-statistics in parentheses.

Table 10: Relationship between physical climate risk measurement error and industry factors. I estimate separate monthly time-series regressions of the unpriced portion of each physical climate risk factor ζ on US industry portfolio returns from Ken French's Data Library. The sample period is from January 2010 to December 2019. Sea proxies for exposure to sea-level rise. Wind proxies for exposure to hurricanes/tropical cyclones. Heat proxies for exposure to heat stress. Rain proxies for exposure to extreme rainfall.

Industry	Sea (ζ_{SEA})	Wind (ζ_{WIND})	Heat (ζ_{HEAT})	Rain (ζ_{RAIN})
Alpha	-0.43	-0.19	0.87	-0.07
	(-2.37)	(-1.45)	(5.10)	(-0.65)
Non-Durables	0.00	0.04	-0.02	0.09
	(0.01)	(0.69)	(-0.14)	(1.47)
Durables	-0.04	-0.02	0.03	-0.02
	(-0.77)	(-0.80)	(0.68)	(-0.47)
Manufacturing	0.04	0.17	0.05	-0.01
	(0.33)	(2.46)	(0.37)	(-0.16)
Energy	0.02	-0.06	-0.08	0.02
	(0.34)	(-2.13)	(-1.12)	(0.82)
High Tech	0.33	-0.12	-0.27	-0.13
	(5.57)	(-3.04)	(-4.46)	(-3.13)
Telecommunication	-0.17	0.07	0.16	0.13
	(-2.36)	(1.35)	(1.98)	(3.35)
Shopping	0.18	0.12	0.12	0.05
	(2.31)	(2.01)	(1.18)	(0.86)
Health	0.29	-0.05	-0.40	-0.24
	(4.76)	(-0.93)	(-5.69)	(-4.81)
Utilities	-0.16	0.03	-0.09	0.13
	(-3.15)	(0.61)	(-1.47)	(3.24)
Other	-0.46	-0.03	0.12	0.21
	(-4.17)	(-0.57)	(1.24)	(3.02)
R^2	0.38	0.16	0.41	0.49

Note: Robust t-statistics in parentheses.

Table 11: Relationship between physical climate risk measurement error and damages from the realisation of severe storms and tropical cyclones. Sea proxies for exposure to sea-level rise. Wind proxies for exposure to hurricanes/tropical cyclones. Heat proxies for exposure to heat stress. Rain proxies for exposure to extreme rainfall. In Panel A, I estimate separate monthly time-series regressions of the unpriced portion of each physical climate risk factor ζ on severe storms in the US with at least $1 billion in estimated damages identified by the National Oceanic & Atmospheric Administration (NOAA). The sample period is from January 2010 to December 2019. In Panel B, I estimate separate monthly time-series regressions of the unpriced portion of each physical climate risk factor ζ on severe storms *and* tropical cyclones in the US with at least $1 billion in estimated damages identified by NOAA. Tropical cyclones are not assessed on their own due to the sparse number of events across the sample. Damages from severe storms and tropical cyclones are likely to be similar, particularly regarding wind damage. The sample period is from January 2010 to December 2019.

Panel A				
Event Damages	Sea (ζ_{SEA})	Wind (ζ_{WIND})	Heat (ζ_{HEAT})	Rain (ζ_{RAIN})
Alpha	-0.33	0.25	0.52	0.48
	(-1.05)	(1.67)	(1.94)	(2.97)
Severe Storm	0.04	-0.08	-0.04	-0.11
	(0.60)	(-2.75)	(-0.71)	(-3.78)
R^2	0.04	0.01	0.01	0.01
Panel B				
Event Damages	Sea (ζ_{SEA})	Wind (ζ_{WIND})	Heat (ζ_{HEAT})	Rain (ζ_{RAIN})
Alpha	0.02	0.31	0.16	0.38
	(0.06)	(1.84)	(0.57)	(2.01)
Severe Storm & Tropical Cyclone	-0.06	-0.08	0.06	-0.07
	(-1.21)	(-4.10)	(1.30)	(-1.66)
R^2	0.00	0.07	0.01	0.03

Note: Robust t-statistics in parentheses. Event damages equal log(damages + 1).

Figures

Figure 1: Cumulative raw performance of the physical climate risk factors. I plot the cumulative monthly raw excess return for each physical climate risk factor constructed using climate exposure scores from *Four Twenty-Seven*. The physical climate risk scores are de-meaned and I use US stocks to build the tradeable risk-factor-mimicking portfolio. Stocks with a positive physical climate risk score are long in the portfolio and stocks with a negative physical climate risk score are short in the portfolio. A stock's weight is determined by its score. The sample period is from January 2010 to December 2019. Sea-level proxies for sea-level rise. Hurricane proxies for hurricane risk. Heat proxies for heat stress. Rain proxies for extreme rainfall.

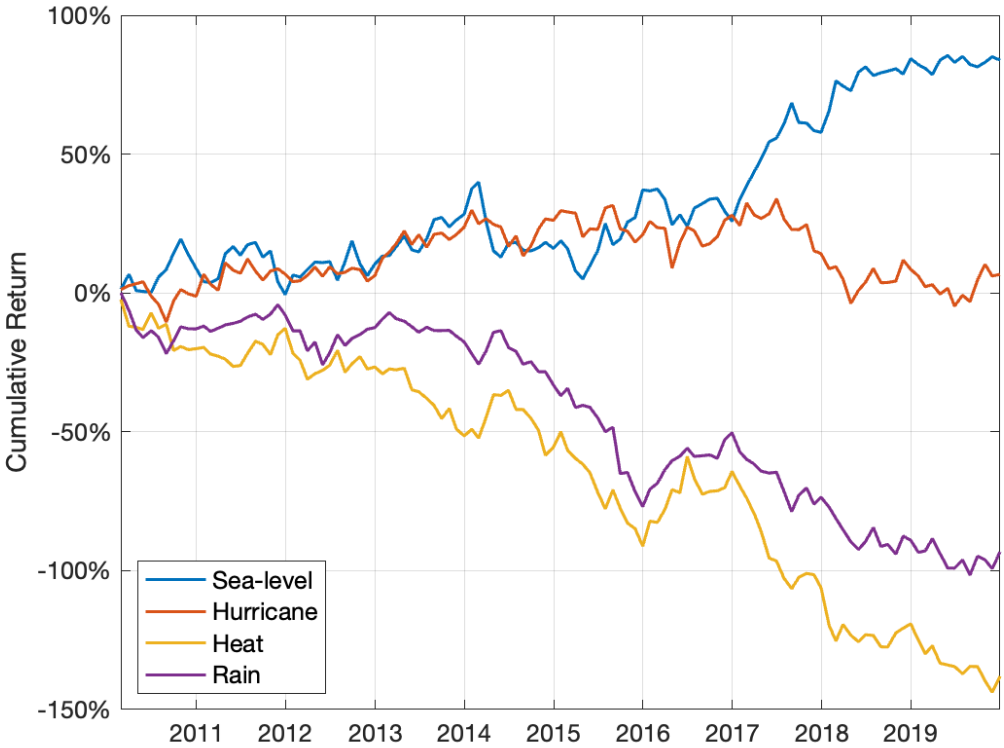


Figure 2: Hurricane risk expected return exposure spread. I plot the monthly annualised expected return of long and short exposure-weighted portfolios along with the exposure spread (the difference between the long and short portfolios). The expected return proxy is the 30-day options measure by Martin and Wagner (2019). The exposure measure is the de-meaned physical climate risk score for exposure to hurricanes/tropical cyclones from *Four Twenty-Seven*. The exposed portfolio weighs stocks by their de-meaned exposure score if that score is positive. The safe portfolio weighs stocks by their de-meaned exposure score if that score is negative. The mean exposure spread across the sample is 0.14%.

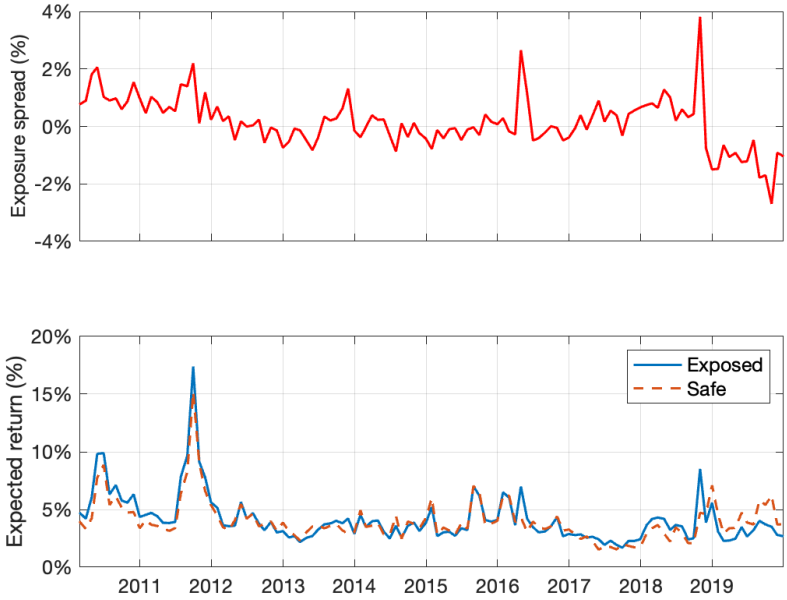


Figure 3: Heat stress expected return exposure spread. I plot the monthly annualised expected return of long and short exposure-weighted portfolios along with the exposure spread (the difference between the long and short portfolios). The expected return proxy is the 30-day options measure by Martin and Wagner (2019). The exposure measure is the de-meaned physical climate risk score for exposure to heat stress from *Four Twenty-Seven*. The exposed portfolio weighs stocks by their de-meaned exposure score if that score is positive. The safe portfolio weighs stocks by their de-meaned exposure score if that score is negative. The mean exposure spread across the sample is -0.002%.

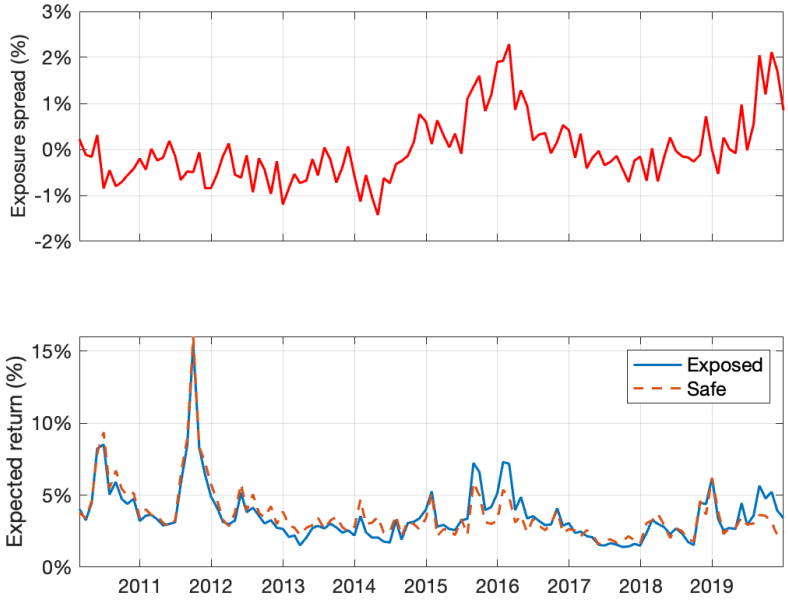


Figure 4: Factor performance with and without error. I first estimate separate monthly time-series regressions of a candidate risk factor on 7 latent priced factors. The candidate risk factors include the excess market return, MKT, the small-minus-big size factor, SMB, the high-minus-low value factor, HML, the robust-minus-weak profitability factor, RMW, the conservative-minus-aggressive investment factor, CMA, a proxy for exposure to sea-level rise, SEA, a proxy for exposure to hurricane risk, WIND, a proxy for exposure to heat stress, HEAT, and a proxy for exposure to extreme rainfall, RAIN. I then plot the priced portion return in blue as the monthly predicted values of the time-series regressions. I also plot the monthly realised return of each candidate risk factor in orange. The sample period is from January 2010 to December 2019.

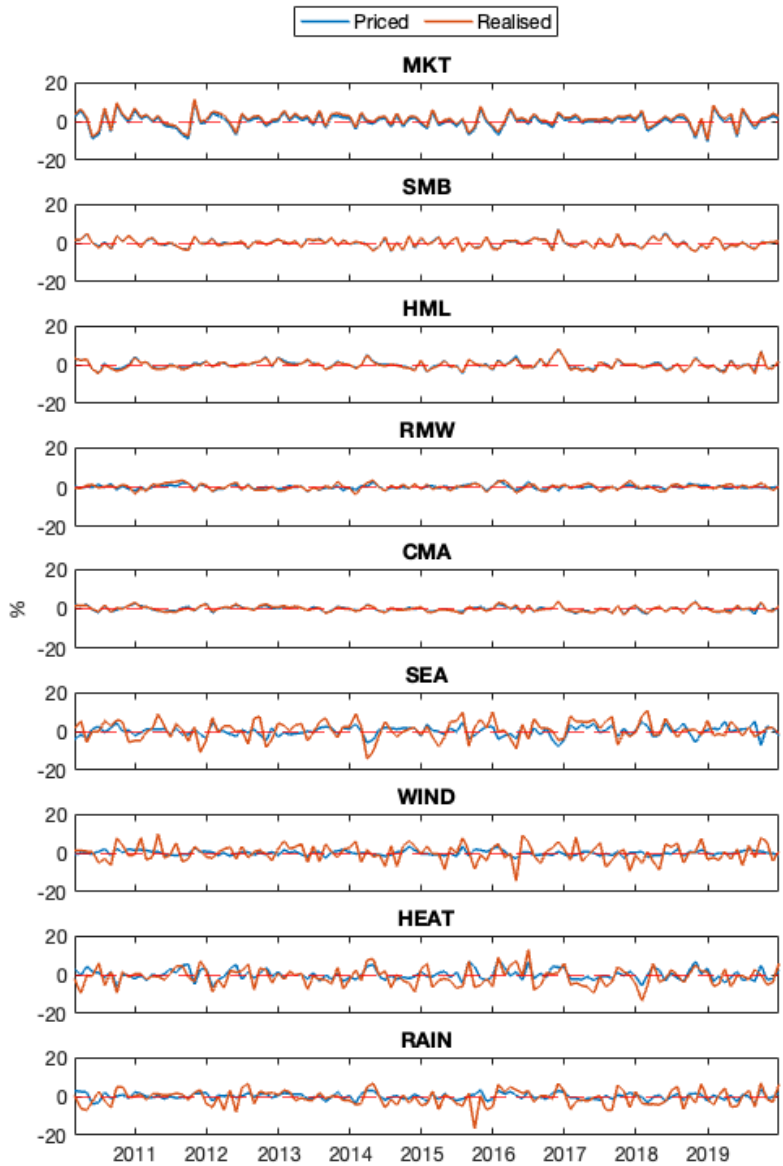
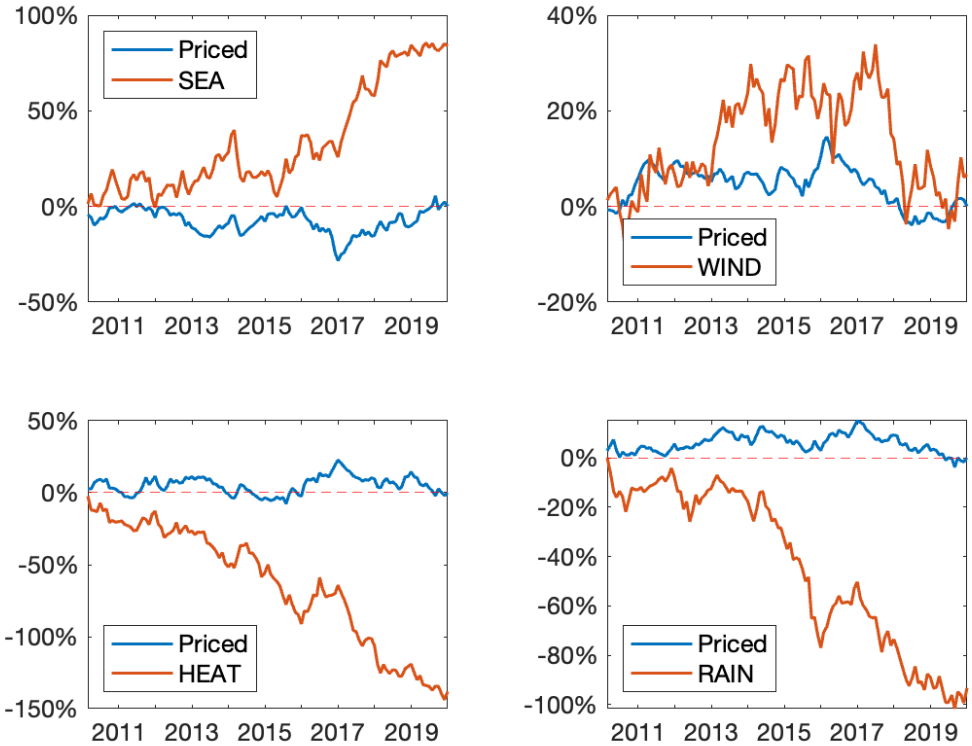


Figure 5: Cumulative physical climate risk factors with and without error. I first estimate separate monthly time-series regressions of the physical climate risk factors on 7 latent priced factors. SEA proxies for exposure to sea-level rise. WIND proxies exposure to hurricane risk. HEAT proxies for exposure to heat stress. RAIN proxies for exposure to extreme rainfall. I then plot the cumulative priced portion return in blue as the monthly predicted values of the time-series regressions. I also plot the cumulative monthly realised return of each physical climate risk factor in orange. The sample period is from January 2010 to December 2019.



Appendix

A: Factor Mimicking Portfolio Construction

This sections provides further details on the construction of the risk-factor-mimicking portfolio.

As shown in Eq. 3 and repeated below in Eq. 13, the following regression is estimated at each period t:

$$\boldsymbol{r}_t = a_t + g_t \boldsymbol{\psi_t} + \boldsymbol{\epsilon}_t, \tag{13}$$

where $t \in [0, T]$, a_t is the intercept, g_t is the proxy variable for exposure to physical climate risk, $\boldsymbol{\psi_t}$ is the vector of cross-sectional firm-level physical climate risk scores, and $\boldsymbol{\epsilon_t}$ is the error term. The estimation of Eq. 13 (in matrix notation to improve exposition) is given by:

$$\begin{bmatrix} \widehat{\alpha}_t \\ \widehat{g}_t \end{bmatrix} = (X'X)^{-1} X' \boldsymbol{r_t}, \tag{14}$$

where $X = [1\, \boldsymbol{\psi}]$. Since the return of a risk-factor-mimicking portfolio is just the sum of the product of each asset's return and its weight in the portfolio, Eq. 14 says that the vector of weights in the risk-factor-mimicking-portfolio at each time t, denoted w_t, is given by $X(X'X)^{-1}$. This can be shown more explicitly as:

$$w_t = \left[\frac{1}{N_t} 1_{N_t} \; \frac{1}{\boldsymbol{\psi}'\boldsymbol{\psi}} \boldsymbol{\psi} \right]. \tag{15}$$

Consequently, the weight given to each firm in the portfolio is given by its physical climate risk score. Firms with a negative de-meaned physical climate risk score have negative weights in the portfolio and firms with a positive de-meaned physical climate risk score have positive weights in the portfolio. The return on the risk-factor-mimicking-portfolio at each time t is then simply $\widehat{g}_t$ from Eq. 13. The standardisation approach adopted in the paper results in a zero-investment portfolio where the risk-factor-mimicking portfolio has unit exposure to physical climate risk.

Because the scale of the physical climate risk scores matters for the scale of the returns, I set the variance

of the scores to one (Fama and French; 2020; Kirby; 2020). Again using matrix notation, Eq. 14 becomes:

$$\begin{bmatrix} \widehat{a}_t \\ \\ \widehat{g}_t \end{bmatrix} = (N_t - 1)^{-1} X' \boldsymbol{r_t}, \tag{16}$$

where $X = [1\, \boldsymbol{\psi}]$.

B: Three-pass Procedure for Estimating Risk Premia

This sections provides further details on the three-pass procedure of Giglio and Xiu (2021).

To obtain the priced risks in the economy, principal component analysis is implemented via a singular value decomposition (SVD) of the matrix $J^{-1}T^{-1}\bar{\boldsymbol{R}}'\bar{\boldsymbol{R}}$, where J gives the number of test assets, T is the length of the time period, and $\bar{\boldsymbol{R}}$ is a matrix of de-meaned returns. The normalised time-series return of each latent factor, $\boldsymbol{f_\kappa}$, where $\boldsymbol{f_\kappa} : [1, K]$, is given by the $K \times T$ matrix $\boldsymbol{\Omega}$:

$$\boldsymbol{\Omega} = T^{0.5}(\boldsymbol{f_1}, ..., \boldsymbol{f_K})'. \tag{17}$$

The loadings on each latent factor are then given by the $J \times K$ matrix $\boldsymbol{B}$:

$$\boldsymbol{B} = T^{-1}\bar{\boldsymbol{R}}\boldsymbol{\Omega}', \tag{18}$$

where I can also use the notation $\boldsymbol{B} : [\boldsymbol{\beta}_1, ..., \boldsymbol{\beta}_K]$, where $\boldsymbol{\beta}_\kappa$ is a $J \times 1$ vector of exposures to the latent factor κ and where $\boldsymbol{\beta_\kappa} : [1, K]$. The number of latent factors is chosen by inspecting the scree plot of the first 15 eigenvalues of the covariance matrix of test asset returns. A statistical procedure can also be implemented to optimise the number of latent factors chosen. Since I use the same test assets as Giglio and Xiu (2021), who utilise the scree plot and a statistical procedure, I also utilise the same number of latent factors.

Equipped with each $\boldsymbol{\beta_\kappa}$, the risk premia of the latent factors are estimated using a cross-sectional OLS regression:

$$\bar{\boldsymbol{r}} = \sum_{\kappa=1}^{K} \lambda_\kappa \boldsymbol{\beta}_\kappa + \boldsymbol{\alpha}, \tag{19}$$

where $\bar{\boldsymbol{r}}$ is a $J \times 1$ vector containing the average return of J test assets, λ_κ is the risk premium estimate for exposure $\boldsymbol{\beta_\kappa}$ to each latent factor, and $\boldsymbol{\alpha}$ is the pricing error. I denote $\hat{\boldsymbol{\lambda}}$ as a $K \times 1$ vector of the latent factor risk premia.

To estimate the exposure of $\boldsymbol{g}$ to each latent factor, a time-series OLS regression of the physical climate risk

factor $\boldsymbol{g}$ on the latent factors $\boldsymbol{\Omega}$ is then estimated:

$$\boldsymbol{g} = \boldsymbol{\eta}'\boldsymbol{\Omega} + \boldsymbol{\zeta}, \quad \text{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) = 0, \tag{20}$$

which is the same as my main identification equation in Eq. 5. This pass identifies the relationship between the physical climate risk factor $\boldsymbol{g}$ and the omitted factors $\boldsymbol{\Omega}$ whilst also controlling for measurement error $\boldsymbol{\zeta}$.

C: Physical Climate Risk Measurement Error

This sections provides further evidence on why physical climate risk measurement error $\boldsymbol{\zeta}$ can be correlated with priced factors $\boldsymbol{\Omega}$.

As motivating evidence, Pankratz et al. (2022) show that both analysts and agents do not fully anticipate heat exposure for geographically-concentrated firms and these firms are correlated with size and investment (priced risks). Basker and Miranda (2017) assess Hurricane Katrina's damage to the Mississippi coast in 2005 and find similar results; small and less-productive firms that incurred damages had lower survival rates. Hong et al. (2019) find that agents do not utilise available information on droughts for assets in the food sector which then impacts asset returns when droughts materialise, thus demonstrating that unpriced risk is correlated with industry. Furthermore, this problem persists even for other well-known risk factors outside the realm of physical climate risk. Daniel and Titman (1997) and Cohen et al. (2003) show that the unpriced portion of the value factor may be related to firm characteristics, causing "entire industries or supply networks to enter the value portfolio at the same time and confound the priced and unpriced portions" (Clarke; 2022, p.176)[38].

I combine these insights with Roll and Ross (1984)'s comment regarding an unpriced cosmetics industry: "since investors can diversify across industries, and since the cosmetics factor is not pervasive, it will not be priced, i.e., it will have no associated risk premium (or one that is immeasurably small)...Almost all [similar candidate factors] are diversifiable and thus are just as irrelevant as if...purely random" (p.349-350). Clarke (2022) thus conclude that the "space of unpriced factors may be extremely large...since any two stocks connected by common unexpected cash flow news, even if there are no implications for expected returns, are connected by a common factor...that may be irrelevant to pricing" (p.162). These common factors can be wide-ranging, such as small stocks being more exposed to hurricanes or, perhaps more pervasively, firms' exposure to physical climate risk being poorly understood or subject to attention shocks (Pástor et al.; 2022).

Indeed, one can only ignore unpriced factors if "the loadings on the priced factors are uncorrelated with the

[38] In practice, the unpriced portion must be explicitly identified so that it can be hedged when constructing risk-factor-mimicking portfolios.

loadings on unpriced factors. If the loadings are instead correlated, the unpriced factor should appear in the asset pricing model and cannot be treated as an ignorable idiosyncratic term, since exposure to the unpriced factor must be hedged from the mean-variance efficient portfolio" (Clarke; 2022, p.162).

D: Historical Geographical Exposure

This section shows how Compustat Segments data is used to calculate, for each firm, their historical geographical exposure.

The Compustat Segments database holds information on over 70% of North American firms and labels each firm's segments consistently over time. This is valuable since there exists no standardised method for disclosing segments despite it being mandatory to disclose this information. Firms can disclose a region, such as Asia, or a particular country, such as Thailand. The consistent labelling by Compustat allows for within-firm comparisons of geographical exposure over time.

To assess geographical exposure, I take firm-level ISIN codes from *Four Twenty-Seven* and convert them to CUSIP codes[39]. Using the CUSIP codes, I collect geographical and operating segment information along with the segment name, geographic segment type, and operating segment type between 1980 and 2021. Observations where the operating segment type is not geographical and where the segment type is referred to as eliminations, consolidation adjustments, unallocated, global export & holding comp, corporate & other, and intra group revenue (i.e. when the segment ID equals 99) are dropped. Then, for each year, I concatenate segment identifiers into a single observation per firm-year, resulting in a string variable that details the geographical segments that are important to the firm.

Consider, for example, the case of *Tesla Inc.* In 2019, the firm disclosed five geographical segments: United States, China, Norway, Netherlands, and Other. The ID's for these segments are 4, 5, 6, 7, and 8, respectively, and the segment string is "4 5 6 7 8". In 2018, the segments are exactly the same as 2019. In 2017, however, Netherlands is not a geographical segment whilst the others remain exactly the same (i.e. the same location and same IDs). The segments string in this case is "4 5 6 7". Colloquially, *Tesla Inc* expanded into the Netherlands in 2018 and hence its physical climate risk exposure is likely to have slightly altered.

It is possible to observe how much segments change over time. To do so, each segment is decomposed by

[39] ISIN codes consist of a 2-digit country code, a CUSIP code, and a 1-digit check number. It is therefore straightforward to extract CUSIP codes from ISIN codes.

splitting each segment ID string into tokens. Simply, the string "1 2 3" is split into the tokens "1", "2", and "3". Then, the intersection between two strings over the union of them (i.e. the Jaccard Index) is calculated, which gives a score that ranges between 0 (no match) and 1 (perfect match). The Jaccard Index, J_{it}, for firm i at time t, is given as:

$$J_{it}(\boldsymbol{s^t}, \boldsymbol{s^b}) = \frac{\boldsymbol{s^t} \cap \boldsymbol{s^b}}{\boldsymbol{s^t} \cup \boldsymbol{s^b}}, \tag{21}$$

where $\boldsymbol{s^t}$ is a vector of location names in year t and $\boldsymbol{s^b}$ is a vector of location names in the benchmark year 2018 (Fletcher et al.; 2018). As an example, the score for *Tesla Inc* between 2018 and 2017 is 0.894 or 89.4%.

After conducting this exercise, the average similarity score for 2005 under a 90%, 80%, and 60% similarity threshold are all at least 0.90. Even under a 60% threshold, the average similarity score is 89% with a standard deviation of 0.13. This implies it is possible to lower the similarity score threshold for firms' geographical segment exposure and still maintain a high average similarity. The similarity score chosen in this paper is 90%.

Supplementary Tables

Table 12: Fama and MacBeth (1973) regressions for estimating risk premia. I estimate separate monthly Fama and MacBeth (1973) two-pass regressions for each physical climate risk factor with the Fama and French (2015) five-factors with no intercept and Shanken-corrected standard errors. MKT-RF is the excess market return. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor. SEA proxies for exposure to sea-level rise. WIND proxies for exposure to hurricane risk. HEAT proxies for exposure to heat stress. RAIN proxies for exposure to extreme rainfall.

	(1)	(2)	(3)	(4)
MKT-RF	1.16	1.12	1.15	1.16
	(3.38)	(3.27)	(3.36)	(3.40)
SMB	-0.06	-0.01	-0.05	-0.06
	(-0.27)	(-0.06)	(-0.25)	(-0.26)
HML	-0.26	-0.25	-0.26	-0.31
	(-1.20)	(-1.15)	(-1.23)	(-1.43)
RMW	0.38	0.31	0.43	0.28
	(1.84)	(1.52)	(2.14)	(1.41)
CMA	-0.07	-0.09	-0.06	-0.07
	(-0.48)	(-0.61)	(-0.39)	(-0.49)
SEA	2.59			
	(2.69)			
WIND		2.72		
		(2.10)		
HEAT			-2.24	
			(-2.97)	
RAIN				-1.20
				(-1.57)
R^2	0.52	0.50	0.48	0.43

Note: Robust t-statistics in parentheses.

Table 13: Giglio and Xiu (2021) three-pass regressions for the Fama and French (2015) five-factors. I estimate monthly risk premia in percent per month for a unit exposure to common risk factors following the three-pass procedure of Giglio and Xiu (2021) that controls for omitted factors and removes measurement error. The sample period is from January 2010 to December 2019. MKT-RF proxies for exposure to market risk. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor. $\bar{\boldsymbol{g}}$ is the mean raw excess return for each factor. γ is the estimated risk premium using K latent priced factors and equals $\hat{\boldsymbol{\eta}}'\hat{\boldsymbol{\lambda}}$; where $\hat{\boldsymbol{\eta}}$ is a vector of factor loadings on each fundamental risk factor and $\hat{\boldsymbol{\lambda}}$ is a vector containing each fundamental risk factor's risk premium.

	Risk Premia Using K Latent Factors							
	$\bar{\boldsymbol{g}}$	$\gamma^{K=1}$	$\gamma^{K=2}$	$\gamma^{K=3}$	$\gamma^{K=4}$	$\gamma^{K=5}$	$\gamma^{K=6}$	$\gamma^{K=7}$
MKT-RF	1.12	0.84	1.13	1.13	1.11	1.11	1.12	1.12
	(3.30)	(2.96)	(4.14)	(4.14)	(4.05)	(4.06)	(4.09)	(4.10)
SMB	-0.04	0.34	-0.09	-0.07	-0.01	-0.01	-0.01	-0.01
	(-0.17)	(3.02)	(-0.46)	(-0.36)	(-0.04)	(-0.06)	(-0.05)	(-0.05)
HML	-0.20	0.15	-0.19	-0.22	-0.24	-0.27	-0.28	-0.28
	(-0.96)	(3.10)	(-1.52)	(-1.09)	(-1.19)	(-1.27)	(-1.31)	(-1.31)
RMW	0.12	-0.14	-0.07	-0.07	0.00	0.01	0.04	0.04
	(0.89)	(-2.89)	(-1.12)	(-1.22)	(0.01)	(0.20)	(0.51)	(0.51)
CMA	0.02	0.02	-0.16	-0.17	-0.06	-0.02	-0.03	-0.03
	(0.13)	(1.51)	(-2.66)	(-1.71)	(-0.53)	(-0.15)	(-0.25)	(-0.25)

Note: Robust t-statistics in parentheses.

Table 14: Relationship between Fama and French (2015) common risk factor measurement error and priced latent factors. I estimate separate monthly time-series regressions of the unpriced portion of each Fama and French (2015) risk factor ζ on K priced latent factors, where $\kappa : [1 : K]$. This tests explicitly whether measurement error ζ in the Fama and French (2015) risk factors is related to priced latent factors K. The sample period is from January 2010 to December 2019. MKT-RF proxies for exposure to market risk. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor.

Latent factors	MKT-RF (ζ_{MKT-RF})	SMB (ζ_{SMB})	HML (ζ_{HML})	RMW (ζ_{RMW})	CMA (ζ_{CMA})
Alpha	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
κ_1	-0.01	-0.02	-0.02	0.30	-0.01
	(-0.58)	(-0.80)	(-0.50)	(4.26)	(-0.16)
κ_2	0.00	-0.02	-0.04	0.13	-0.07
	(0.17)	(-0.84)	(-0.63)	(2.59)	(-1.21)
κ_3	0.00	-0.01	0.05	0.16	0.10
	(0.02)	(-0.34)	(1.75)	(2.33)	(2.05)
κ_4	0.00	0.00	0.00	-0.16	-0.06
	(0.01)	(-0.08)	(0.05)	(-4.06)	(-1.47)
κ_5	0.00	0.00	0.01	-0.11	-0.07
	(-0.01)	(0.05)	(0.30)	(-2.15)	(-1.75)
κ_6	0.00	0.00	0.01	-0.32	0.03
	(-0.01)	(-0.02)	(0.22)	(-6.33)	(0.67)
κ_7	0.00	0.00	0.00	0.07	0.01
	(0.00)	(0.03)	(-0.11)	(1.86)	(0.21)
R^2	0.00	0.01	0.03	0.49	0.12

Note: Robust t-statistics in parentheses.

Supplementary Figures

Figure 6: Eigenvalues of the covariance matrix of test asset returns. I plot the logarithm of the first 15 eigenvalues of the covariance matrix of 32 US value-weighted equity portfolio returns triple-sorted on size, book-to-market, and investment from Ken French's Data Library. The sample period is from January 2010 to December 2019.

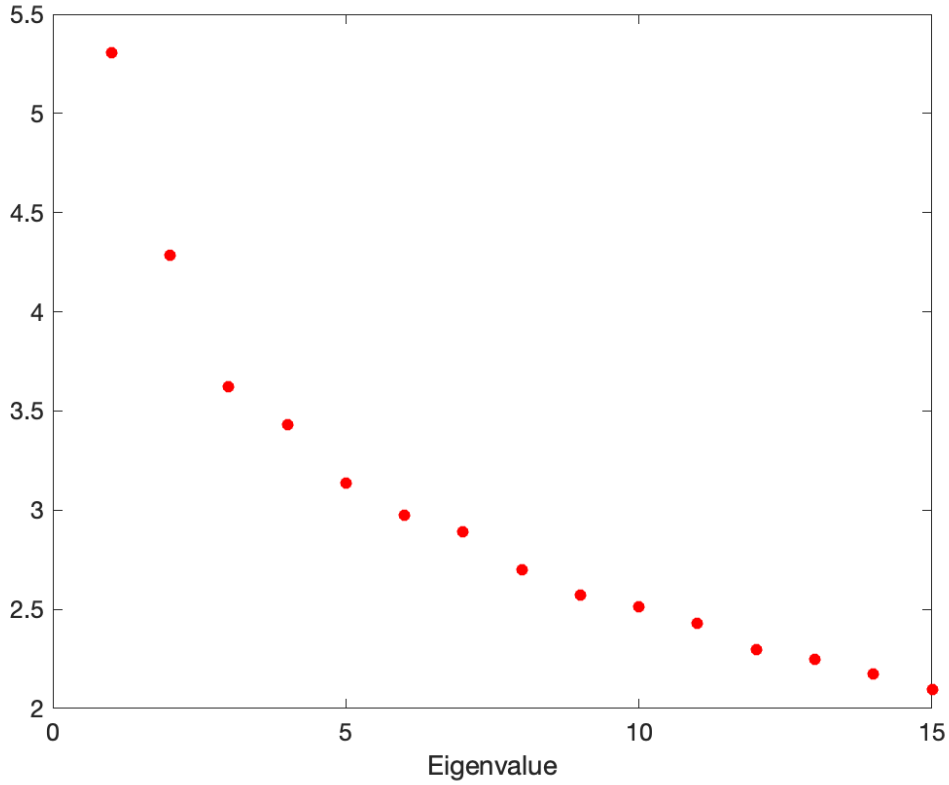


Figure 7: priced portion of observed factors proxied by R^2. I first estimate separate monthly time-series regressions of each candidate risk factor on K priced latent factors. The sample period is from January 2010 to December 2019. The R^2 from each regression proxies for the variation in the candidate risk factor that is priced. I then plot the R^2 for each regression under different assumptions of the number of priced latent factors that exist in the data. MKT-RF is the excess market return. SMB is the small-minus-big size factor. HML is the high-minus-low value factor. RMW is the robust-minus-weak profitability factor. CMA is the conservative-minus-aggressive investment factor. These initial five factors provide a benchmark that I compare the physical climate risk factors to. SEA proxies for exposure to sea-level rise. WIND proxies for exposure to hurricanes/tropical cyclones. HEAT proxies for exposure to heat stress. RAIN proxies for exposure to extreme rainfall.

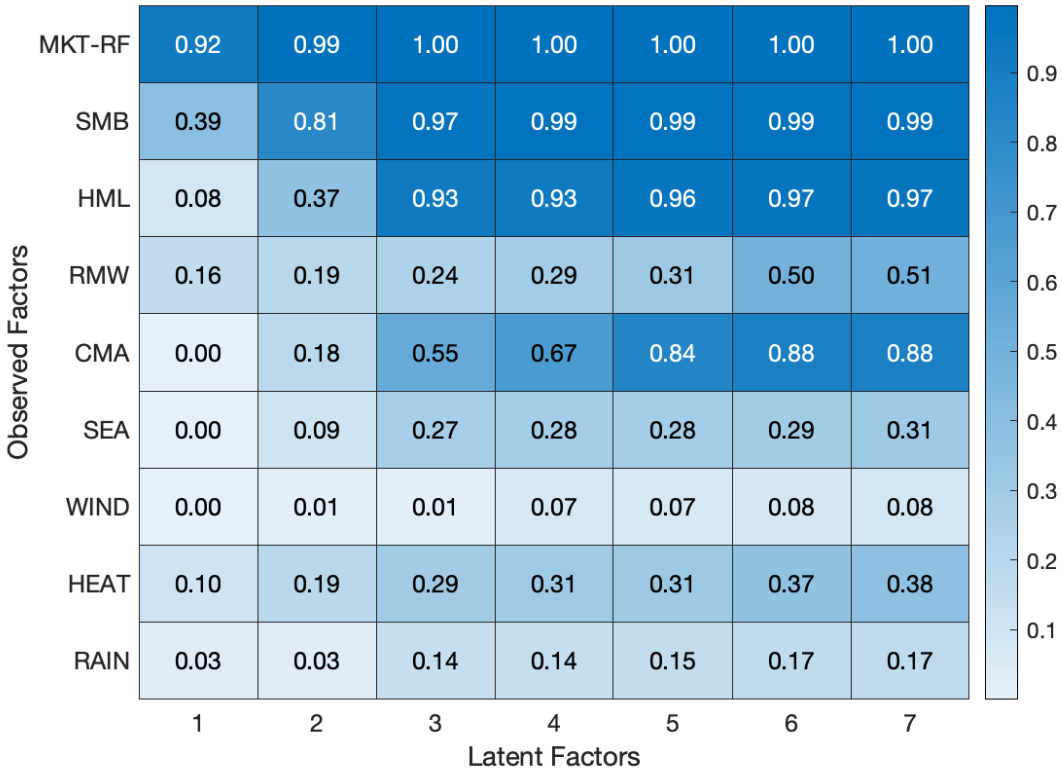


Figure 8: Cumulative difference between the realised and priced portion of each physical climate risk factor. I first estimate separate monthly time-series regressions of the physical climate risk factors on 7 latent priced factors. SEA proxies for exposure to sea-level rise, WIND proxies exposure to hurricane risk, HEAT proxies for exposure to heat stress, RAIN proxies for exposure to extreme rainfall. I then plot the cumulative difference between the realised return of each physical climate risk factor and its estimated priced portion for each physical climate risk factor. In other words, the error term, ζ, from the time-series regressions. The sample period is from January 2010 to December 2019.