Pricing Physical Climate Risk in the Cross-Section of Returns

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Abstract

Using location-specific climate exposure measures, we test for the existence of physical climate risk premia. We provide suggestive evidence that the priced portion of hurricane risk commands a positive premium whilst the priced portion of heat stress commands a negative premium. Both exposure to sea-level rise and exposure to extreme rainfall command no risk premium. Most of the innovations in physical climate risks appear mispriced. The unpriced portions of physical climate risks co-vary with priced latent factors, suggesting agents struggle to price the risk, and can be explained by industry returns, common risk factors, and realisations 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". Similarly, 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). Institutional investors consequently believe physical climate risks[1] are under-priced (Krueger et al.; 2020) and regulators are attempting to mandate the disclosure of "certain climate-related information, including information about climate-related risks that are reasonably likely to have material impacts" (SEC; 2022, p.42).

Concurrently, standard asset-pricing theory posits agents should be compensated for holding assets exposed to *undiversifiable* bad states of nature. These state of nature may include, quite literally, physical climate risks such as severe weather events. Agents value holding assets unexposed to severe weather events because they act as good hedges, thus the price of these assets should be high and their expected returns low. Assets that are exposed to severe weather events should, on average, reward agents for bearing risk.

However, despite the policy imperative, confusion exists over whether agents can incorporate information about climatic conditions and firm-level outcomes into their decision-making when they price assets, meaning it is also unclear if physical climate risk is priced as a systematic risk factor[2]. For example, agents appear to react to various severe weather events in their local area but then forget about them (Alok et al.; 2020). They also appear to struggle to price predictable negative weather-related events such as extreme heat and droughts (Pankratz et al.; 2021; Hong et al.; 2019). For some particular risks, such as hurricanes, reactions can persist in the long-run as agents learn about exposure (Addoum et al.; 2021; Kruttli et al.; 2021). Overall, such confusion supports claims that the *translation* of climate science into actionable information for non-experts is difficult (Fiedler et al.; 2021).

[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). In situations where agents can easily diversify their portfolios to reduce exposure to severe weather events, there is no expectation that exposure to such a risk should compensate agents.

There are perverse risks to potential mispricing. First, under- or over-investment in the real economy can occur if assets are mispriced due to distorted price signals (Van Binsbergen and Opp; 2019). Such distortions emerge because agents under-react to true exposure, such as drought risk, which lowers the cost-of-capital for exposed firms and allows them to continue investing in risky projects[3]. Second, agents can affect the cost-of-capital of exposed firms by tilting their portfolios to unexposed firms (Pástor et al.; 2020). However, they can only do so if they know which firms are exposed.

An important problem to *testing* the pricing of physical climate risk has been the the complexity of understanding true exposure. Berg et al. (2021) provide evidence that ESG[4] ratings have high variance due to disagreements on asset exposure and on the weighting that specific issues have in aggregated scores, which induces measurement error from the econometrician when they rely on scores from ratings providers. Approaches that rely on firm disclosures may be noisy since filings are known to contain boilerplate statements that provide vague statements about future exposure (Campbell et al.; 2014)[5] or may be crowded out by other events such as the case with earnings calls during the COVID-19 pandemic (Sautner et al.; 2020). Of the measures that do not rely on firm communication to estimate exposure to physical climate risk, a further frustration arises with the lack of information on the geographical footprint of the firm. Many assessments of exposure utilise firm-headquarters as a proxy for the firm's geography to combat this (Hong et al.; 2019; Zhang and Zhu; 2020; Griffin et al.; 2019) or have to limit the geography to certain regions (Addoum et al.; 2020; Braun et al.; 2021; Pankratz et al.; 2021).

This paper consequently studies whether physical climate risk is priced as a systematic risk factor, and makes two contributions. First, new and specific physical climate risk factors are constructed 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 t. These factors use firm-level physical climate risk scores obtained from climate data vendor *Four Twenty-*

[3]For example, in a similar case, the mispricing of distressed stocks is linked with excess investment and excess external financing (Avramov et al.; 2022).

[4]ESG stands for environmental, social, and governance.

[5]Despite this, Nagar and Schoenfeld (2022) provide evidence that annual reports provide useful information on weather exposure.

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 improves on measures that rely on firm disclosures, news, the location of headquarters, or attempting to aggregate physical climate risk with other topics.

Second, instead of attempting to specify the true asset-pricing model when estimating whether any physical climate risk premium exists, the three-pass procedure of Giglio and Xiu (2021) is used to control for omitted factors and measurement error. This approach extracts latent factors from the covariance matrix of test asset returns and the exposures to each identified factor, thus identifying all omitted factors and eliminating omitted variable bias. An important benefit of this approach is the ability to explicitly tackle the issue of measurement error: instead of assuming measurement error arises from mistakes in the econometrician's measurement of a candidate risk factor (classical measurement error), we test if errors arise from agents when they price physical climate risk (non-classical measurement error). This alternative interpretation holds when measurement error in the physical climate risk factors is correlated with priced factors.

The key results are as follows. The monthly excess return of physical climate risk factor-mimicking portfolios in the US equity market between January 2010 and December 2019 are 0.70%, 0.06%, -1.16%, and -0.78% for a unit exposure to sea-level rise, hurricane risk, heat stress, and extreme rainfall risk, respectively. The realised performance of the factors during major events appear to follow the theoretical predictions: that is, their cumulative performance is positive prior to the event, negative during the event, and positive again after the event. However, this does not necessarily mean these factors compensate agents with higher returns on aggregate. Indeed, the main result is that the estimated risk premium for hurricane risk is 0.39% per month whilst it is -0.59% per month for heat stress. There is no significant risk premium associated with exposure to sea-level rise and extreme rainfall. For comparison, the estimated monthly risk premium for the market factor over the sample is 1.12%. The market risk premium is very close to the realised average monthly performance of the market portfolio (as expected), and this is also true for other common risk factors such as size, value, profitability, and investment. However, the realised monthly average performance of the physical climate risk factors differs greatly from their risk premia: the priced portion of innovations in the physical climate risk factors are only between 8% - 38% of their total variance compared to approximately 100% for the market, size, value, profitability, and investment factors. Crucially, there is indicative evidence that this is not due to noise (classical measurement error) since the errors in the physical climate risk factors co-vary significantly with priced latent factors. The tentative 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 may struggle to price material physical climate risks.

This paper contributes to various strands of literature. First, a growing area of research constructs risk-factor-mimicking portfolios for physical climate risks to estimate whether exposure to such a risk can explain the cross-section of returns. 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. (2021) build similar long-short portfolios derived from the proportion of earnings calls spent discussing climate risks but find no significant premium. 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 portfolios using the slope coefficient of returns regressed on aggregate hurricane loss growth and identify a significantly positive premium (0.74% per month). Similar effects are found in this paper despite using a completely new source of data and a new empirical approach. Indeed, the most similar paper to ours in terms of data quality is Ginglinger and Moreau (2019). However, they assume that their cross-sectional physical climate risk data is accurate over an extended time period. In this paper, geographical segment data is used to subset the sample to only include firms that have not changed their geographical exposure by more than 90% from when the cross-sectional data is collected.

The second 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. Furthermore, climate scientists have high confidence in the thermodynamic aspects of climate change (e.g. "the earth is warming"), yet there exists much lower confidence in dynamic aspects (e.g. "where and how strong a storm is") (Shepherd et al.; 2018). Excessive trust may then be placed in vague long-term climate predictions that may not contain an exhaustive set of possible material risks (Fiedler et al.; 2021). Such risks may also be idiosyncratic and *dynamic*: they change depending on a firms' resilience and on climate dynamics (Freiberg et al.; 2020).

Relatedly, the third strand of literature this paper contributes to is the issue of measurement error, more broadly, in asset-pricing. We disentangle the priced and unpriced portion of candidate physical climate risk factors by assessing explicitly the issue of measurement error: as long as the unpriced portion of a factor co-varies with priced latent factors, the (non-classical) measurement error may indicate error by agents rather than by the econometrician. Clarke (2022), Giglio and Xiu (2021), and Daniel et al. (2020) all contribute a similar framework to the problem: a candidate risk factor that can be split into a priced component and an unpriced component. Indeed, "while unpriced common factors may be interesting in their own right, they are not likely to be central puzzles in the intersection of macroeconomics and finance" (Clarke; 2022, p.161). In this paper, they are of particular interest and attention is specifically paid towards whether measurement error is classical or non-classical. Our indicative results consequently speak to the warning of measurement error by Novy-Marx (2014, p.143-144):

> "Standard predictive regressions fail to reject the hypothesis that the party of the US President, the weather in Manhattan, global warming, El Niño, sunspots, or the conjunctions of the planets are significantly related to anomaly performance. These results are striking and surprising. In fact, some readers might be inclined to reject some of this paper's conclusions solely on the grounds of plausibility. I urge readers to consider this option carefully, however, as doing do so entails rejecting the standard methodology on which the return predictability literature is built."

Whilst this paper avoids assessing the full economic channel in which physical climate risk impacts asset returns, there is preliminary evidence that these risks are material when the pricing errors appear related to priced latent factors in returns (non-classical measurement error).

2 Theory and Risk Factor Construction

To determine the expected sign of the physical climate risk premium, the theoretical asset-pricing model with climate risk proposed by Pástor et al. (2020) is provided to guide the analysis.

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[6].

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[7]. The intuition for this result is relatively straightforward. Unexpected 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

[6] 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.

[7] A theoretical solution for how climate risks may affect expected returns is provided by Pastor et al. (2020, Appendix, p.20-21).

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.

2.1 Building the Physical Climate Risk Factor

We 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 econometrician (Jensen et al.; 2021).

Fama and French (2020) show that a cross-sectional approach, which 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[8]. 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. (2021), Bolton and Kacperczyk (2021), and Lioui and Tarelli (2021).

The necessary inputs to construct such a cross-sectional factor include a vector of cross-sectional firm-level physical climate risk scores $\boldsymbol{\psi}$ and a vector of cross-sectional excess asset returns $\boldsymbol{r_t}$ measured at each period t. The physical climate risk scores are time-invariant to reflect the fact physical climate risk exposure is

[8]See Lioui and Tarelli (2021) for a review of this matter related to "green" factors.

relatively stationary. The sample of stocks at each time period t is given as N_t, such that $\boldsymbol{r_t} = [r_i, ..., r_N]$ at each time t. Following Fama and French (2020) and Lioui and Tarelli (2021), we de-mean (standardise) the physical climate risk scores:

$$\sum_{i=1}^{N_t} \psi_i = 0. \tag{3}$$

Then, the following cross-sectional regression is estimated at each time t:

$$\boldsymbol{r}_t = a_t + g_t \boldsymbol{\psi} + \boldsymbol{\epsilon}_t, \quad i.i.d.\ \boldsymbol{\epsilon_t} \sim \mathscr{N}(0, 1), \tag{4}$$

where $t \in [0, T]$, a_t is the intercept, g_t is the proxy variable for exposure to physical climate risk, $\boldsymbol{\psi}$ is a vector of cross-sectional firm-level physical climate risk scores, and $\boldsymbol{\epsilon_t}$ is the error term. The return of the physical climate risk factor at each period t is $\widehat{g}_t$. To see this, note that the estimation of Eq. 4 (in matrix notation) is given by:

$$\begin{bmatrix} \widehat{\alpha}_t \\ \\ \widehat{g}_t \end{bmatrix} = (X'X)^{-1} X' \boldsymbol{r_t}, \tag{5}$$

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 it's weight in the portfolio, Eq. 5 says that the vector of weights in the risk-factor-mimicking-portfolio at each time t, denoted w_t, is given by $(X'X)^{-1}X'$. This can be shown more explicitly as:

$$w_t = \left[\frac{1}{N_t} 1_{N_t} \, \frac{1}{\boldsymbol{\psi}'\boldsymbol{\psi}} \boldsymbol{\psi} \right]. \tag{6}$$

Consequently, the weight given to each firm in the portfolio is given by it's 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. 4. The standardisation approach adopted here results in a zero-investment portfolio where the risk-factor-mimicking portfolio has unit exposure to physical climate risk. The estimated intercept, $\widehat{a}_t$, is the cross-sectional mean of the asset returns: $\frac{1'_{N_t} \boldsymbol{r_t}}{N_t}$ at each time t.

Because the scale of the physical climate risk scores matters for the scale of the returns, we standardise the factor to have unit variance (Fama and French; 2020; Kirby; 2020). Using matrix notation, Eq. 5 then becomes:

$$\begin{bmatrix} \widehat{a}_t \\ \widehat{g}_t \end{bmatrix} = (N_t - 1)^{-1} X' \boldsymbol{r_t}, \tag{7}$$

where $X = [1\, \boldsymbol{\psi}]$. In all further notation for $\widehat{g}_t$, the paper shall use the vector $\boldsymbol{g} = [\hat{g}_0, ..., \hat{g}_T]'$ to denote its time-series innovations.

2.2 Drivers of the Physical Climate Risk Factor

The expected premium for a unit exposure to physical climate risk is positive. Recalling that the factor $\boldsymbol{g}$ is equal to climate sensitivity $\bar{c} \equiv \bar{\boldsymbol{g}} > 0$, this section identifies two wedges that drive risk in the factor. This is important since it will help describe why the performance of the factor may deviate from its expected sign.

First, agents' climate sensitivity $\bar{c}$ may experience attention shocks from unexpected events not driven by severe weather, driving the realised performance of the factor to be different from its expected performance. These shocks can take the form of key reports that outline the potential for severe weather events in the future. For example, Painter (2020) find that the release of the Stern Review on the Economics of Climate Change, a report for the UK government on the effects of climate change on the world economy, led to an increase in issuance costs for climate-affected bonds as investors updated their sensitivity to climate risks. Choi et al. (2020) further find that individual investors respond to (unexpected) abnormally hot days by selling stocks with high carbon emissions. Agents do so because they are attention-constrained and the heat shock acts as a climate "wake-up" call that updates their climate sensitivity. It is plausible that agents would also sell physically-exposed stocks for the same reason. Indeed, Bortolan et al. (2022) find that investors react to deviations in temperature variability across space. Attention shocks are represented simply as:

$$[\theta^* - \theta], \tag{8}$$

where θ is the expectation of severe weather events and θ^* is the realised sensitivity to severe weather events. Unexpected shifts in the sensitivity to severe weather change the demand for exposed and unexposed assets, leading to temporary realised returns that differ from expectations.

Panel A in Figure 1 shows visually how attention shocks can drive the physical climate risk factor. As shown, climate sensitivity is measured as 0.1 from period 1 to period 5 until a positive shock arrives in period 6. This shock could be the Stern Review or a new report outlining risks to climate change, such as assessments from the Intergovernmental Panel on Climate Change (IPCC). Climate sensitivity consequently shifts to a higher level, 0.3, and stays at this level *permanently* as agents internalise the new information.

Second, agents' climate sensitivity $\bar{c}$ may suffer from unexpected mispricing. This arises because it is difficult to measure firm-level physical climate risk exposure. For example, agents not only have to know the full geographical extent of a firm's operations but also the materiality of the physical climate risks the firm faces in order to assess exposure. Such information is not currently required to be disclosed in full detail and, in the latter case of materiality, requires intricate knowledge on the firm's ability to withstand physical climate risks.

Evidence for such mispricing is nascent. Hong et al. (2019) find that agents do not react to predictably worsening drought conditions for agricultural stocks until *after* unexpected droughts materialise, thus suggesting agents only learn from realised events. Pankratz et al. (2021) further find that, despite historical evidence of a negative relationship between extremely hot days and firm outcomes, analysts and investors are surprised when unexpected negative results are announced by exposed firms. Khan et al. (2016) find that firms with poor ratings on *material* sustainability issues underperform firms with high ratings, suggesting material sustainability issues drive performance but is not expected to do so by agents. Mispricing shocks are consequently represented as:

$$[\upsilon^* - \upsilon], \tag{9}$$

where υ is the expectation of exposure to physical climate risk and υ^* is the realisation of exposure.

Panel B in Figure 1 demonstrates the case in which the physical climate risk exposure of stocks is unexpectedly mispriced. Unlike Panel A, climate sensitivity from period 1 to period 5 is now measured as 0 to reflect the fact agents do not consider any asset exposed. In period 6, a temporary unexpected shock arrives such as a severe hurricane or flood. Agents react to the shock and climate sensitivity shifts to -0.1, much like the reactions evidenced by Hong et al. (2019) and Pankratz et al. (2021). However, the reaction is short-lived and climate sensitivity returns to 0 in period 7. The same phenomenon happens when another shock occurs in period 9. The time-series of the physical climate risk factor in this state will thus display continued negative performance as agents are unable to rationally price the assets[9].

In sum, important drivers of the physical climate risk factor can be summarised as:

$$\bar{g} = [\theta^* - \theta] + [\upsilon^* - \upsilon], \tag{10}$$

where $\bar{g} = \bar{c}$ and realised innovations in physical climate risk are driven by shocks to attention $[\theta^* - \theta]$ and mispricing $[\upsilon^* - \upsilon]$[10].

[9]Panel C in Figure 1 also shows visually how uncertainty can drive the physical climate risk factor, although this is a less important driver than attention and mispricing. As shown, climate sensitivity is measured as 0.1 from period 1 to period 5. In period 6, an unexpected shock arrives that shifts climate sensitivity to -0.2 which persists into period 7. As agents update their expectations about physical climate risk from the severe shock, climate sensitivity shifts to 0.1 as agents are compensated for holding assets exposed to the shock that began in period 6. The overall effect is an increase in the variance and performance of the physical climate risk factor.

[10]The sample period selected to estimate the physical climate risk premium will also be important. If severe weather events are frequent across the sample, they can dominate the estimation of risk premia and lead to a biased estimate. For example, Pástor et al. (2021) argue that an ESG risk-factor-mimicking portfolio that buys "green" firms and sells "brown" firms only outperforms because it is measured during a period with many positive attention shocks. To control for this, the paper utilises a long time-series and also assesses the temporal variation of severe weather events.

3 Empirical Strategy

We now provide the approach to estimate physical climate risk premia.

3.1 The Three-Pass Procedure

Consider first a multi-factor asset-pricing model that says the time-series excess return of asset j, $\boldsymbol{r_j}$, where $j : [1, J]$, depends on its exposure to common risk factors:

$$\boldsymbol{r_j} = q_j + \beta_j \boldsymbol{g} + \sum_{\kappa=1}^{K} \beta_{\kappa,j} \boldsymbol{f_\kappa} + \boldsymbol{\epsilon_j}, \quad i.i.d.\ \boldsymbol{\epsilon_j} \sim \mathcal{N}(0, 1), \tag{11}$$

where q_j is the intercept, β_j is exposure to the physical climate risk factor $\boldsymbol{g}$, $\beta_{\kappa,j}$ is exposure to the κ latent factor, $\boldsymbol{f_\kappa}$, where $\boldsymbol{f_\kappa} : [1, K]$, and $\boldsymbol{\epsilon_j}$ is the error term. The aim of the test asset $\boldsymbol{r_j}$ is to produce a large dispersion in returns that are to be explained by the model (Cochrane; 2009)[11] and their exposure to common risk factors can be estimated using time-series OLS.

The usual two-pass procedure to estimate risk premia assumes the econometrician knows, a-priori, the full asset-pricing model (Fama and MacBeth; 1973). However, specifying the correct asset-pricing model is difficult owing to the plethora of identified common risk factors (Cochrane; 2011; Harvey et al.; 2016). As long as an omitted factor is correlated with physical climate risk and the test assets, then the estimated risk premium will be biased. For example, Pástor et al. (2021) 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 physical climate risks such as extreme weather events. The risk premium estimate will consequently be biased if any of these factors are omitted from the asset-pricing model. In reality, the literature is infant regarding the link between physical climate risk and other common risk factors, implying a high chance of omitted variable bias induced by the econometrician.

[11]It is common practice to utilise portfolios as test assets in order to combat the errors-in-variables problem; where the betas in Eq. 11 are estimated with some degree of error which is attenuated when using individual assets (Jensen et al.; 1972).

Another issue arises with the measurement of the physical climate risk factor itself. Roll (1977) provide one of the earliest critiques that a mis-measured proxy for a particular risk can lead to incorrect inference on its risk premia[12]. Agents may perceive, and thus price, risk from a proxy factor very differently than the true factor. The econometrician, however, assumes such a factor is measured accurately and incorrectly draws the conclusion that the factor commands a small or insignificant premium.

The idea of both omitted factors and measurement error is captured by the following equation:

$$\boldsymbol{g} = \boldsymbol{\eta}'\boldsymbol{\Omega} + \boldsymbol{\zeta}, \quad \mathrm{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) = 0, \tag{12}$$

where $\boldsymbol{g}$ is a $T \times 1$ vector of the observed physical climate risk factor, $\boldsymbol{\eta}$ is a $K \times 1$ vector of the relationship between the realised physical climate risk factor and the $K \times T$ matrix of priced omitted factors $\boldsymbol{\Omega}$, and $\boldsymbol{\zeta}$ is a $T \times 1$ vector containing measurement error. Importantly, measurement error $\boldsymbol{\zeta}$ is assumed to be classical in that it is unrelated to the omitted (latent) factors $\boldsymbol{\Omega}$: measurement error only arises from the inability of $\boldsymbol{g}$ to capture material exposure.

Given the presence of omitted factors and measurement error, the risk premium of $\boldsymbol{g}$, γ, is given by $\hat{\boldsymbol{\eta}}'\hat{\boldsymbol{\lambda}}$, where $\hat{\boldsymbol{\lambda}}$ is a $K \times 1$ vector of latent factor risk premia. Since $\hat{\boldsymbol{\eta}}$, the relationship between the observed physical climate risk factor and any omitted factors, is *unobserved*, the estimated risk premium clearly becomes difficult to obtain. However, Giglio and Xiu (2021) show that, owing to a general rotation invariance result, latent factors and their loadings can be obtained given only the matrix of asset returns $\boldsymbol{R}$ to obtain the risk premium of $\boldsymbol{g}$[13]. Because the physical climate risk premium is invariant to how other control factors are rotated, it is not necessary to specify the full asset-pricing model when controlling for both omitted factors and measurement error.

[12]The issue is caused, in the case of Roll (1977), because a proxy for market risk must contain all investable assets, yet commonly only includes a market index. The market index, which is usually value-weighted, can be dominated by a few mega-cap stocks that partly drive innovations in the index due to firm-specific risks. Consequently, the proxy for market risk is not fully diversified and idiosyncratic risks can drive its return rather than *true* common systematic risk. Another issue arises when the proxy for market risk does not include *all* investable assets, such as the housing stock.

[13]The use of dimension-reduction techniques to obtain latent factors in asset-pricing is well-documented and is becoming increasingly adopted (e.g. Kozak et al. (2018)). See Kelly et al. (2021, p.7-11) for a review of these methods applied in an asset-pricing context.

K latent factors are obtained through principal component analysis (PCA) by identifying latent factors and their loadings, where 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. Following Giglio and Xiu (2021), PCA is then 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 $\boldsymbol{\Omega}$:

$$\boldsymbol{\Omega} = T^{0.5}(\boldsymbol{f_1}, ..., \boldsymbol{f_K})'. \tag{13}$$

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

$$\boldsymbol{B} = T^{-1}\bar{\boldsymbol{R}}\boldsymbol{\Omega}', \tag{14}$$

where we 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 $\boldsymbol{\beta_\kappa} : [1, K]$. Equipped with each $\boldsymbol{\beta_\kappa}$, the risk premia of the latent factors are estimated using a cross-sectional OLS regression:

$$\bar{\boldsymbol{r}} = \sum_{\kappa=1}^{K} \lambda_\kappa \boldsymbol{\beta}_\kappa + \boldsymbol{\alpha}, \tag{15}$$

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. We 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:

$$\boldsymbol{g} = \boldsymbol{\eta}'\boldsymbol{\Omega} + \boldsymbol{\zeta}, \quad \mathrm{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) = 0, \tag{16}$$

which is the same as our main identification equation in Eq. 12. 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 $\boldsymbol{\zeta}$. Importantly, we assume measurement error is classical: $\mathrm{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) = 0$. The estimated risk premium in the three-pass procedure is then:

$$\gamma = \hat{\boldsymbol{\eta}}'\hat{\boldsymbol{\lambda}}, \tag{17}$$

and is the primary risk premium estimate used in this paper.

3.2 Measurement Error

The time-series pass (Eq. 16) is particularly useful since it provides the priced portion of the physical climate risk factor $\boldsymbol{g}$:

$$\widehat{\boldsymbol{g}} = \hat{\boldsymbol{\eta}}'\boldsymbol{\Omega}, \tag{18}$$

as well as the measurement error of $\boldsymbol{g}$:

$$\boldsymbol{\zeta} = \boldsymbol{g} - \hat{\boldsymbol{\eta}}'\boldsymbol{\Omega}. \tag{19}$$

The R^2 obtained from regressing the physical climate risk factor on the latent factors (Eq. 16) is also informative because it quantifies the proportion of the variance that can be explained by the latent (priced) factors. Because of the rotation invariance result, the latent factors span priced risk factors, up to latent factor K.

To aid interpretation, Giglio and Xiu (2021) suggest to view the unpriced portion of the factor $\boldsymbol{\zeta}$ as "measurement error that captures exposure to unpriced risk or idiosyncratic risk that is not fully diversified" (Giglio and Xiu; 2021, p.1955). 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[14]. Measurement error thus represents *unpriced* risk that is driven by some *common variation* in the returns of the physical climate risk factor. That is, it is common variation across stocks "unaccompanied by a return premium" (Clarke; 2022, p.159).

Daniel et al. (2020) show that one can only ignore the unpriced portion of the physical climate risk factor when the priced factors $\boldsymbol{\Omega}$ are uncorrelated with the unpriced portion of the factor. To see this, recall the

[14] 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). Also note that this paper builds a *traded* factor from investable assets. Un-priced portions of *un-traded* factors, such as aggregate liquidity and gross domestic product, are arguably more plausible given that these factors give a lot of freedom to the econometrician, as evidenced by Giglio and Xiu (2021, Appendix, Section III.8). It is thus interesting when even a traded factor has large measurement error that is *not* pure noise.

main model specification used in this paper, which follows closely Clarke (2022), Giglio and Xiu (2021), and Daniel et al. (2020), is given by:

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

An explicit assumption is that measurement error $\boldsymbol{\zeta}$ is classical measurement error: it is idiosyncratic to physical climate risk and is not correlated with any other risk factors $\boldsymbol{\Omega}$. For example, it may capture the poor data availability to assess exposure to physical climate risk.

However, the covariance between measurement error and other factors may not be zero, leading to non-classical measurement error. Pankratz et al. (2021) show that both analysts and agents do not fully anticipate heat exposure for geographically-concentrated firms which themselves are correlated with size and investment (well-established risk factors). Basker and Miranda (2017) assess Hurricane Katrina's damage to the Mississippi coast in 2005 and find similar results; small and less-productive firms (well-established risk factors) 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 (a well-established risk factor). Furthermore, this problem persists even for other well-known risk factors. 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)[15].

A time-series regression can be estimated to test the association between measurement error and the priced factors:

$$\boldsymbol{\zeta} = d + \boldsymbol{\chi}'\boldsymbol{\Omega} + \boldsymbol{\epsilon}, \quad i.i.d.\ \boldsymbol{\epsilon} \sim \mathcal{N}(0,1). \tag{20}$$

where $\boldsymbol{\zeta}$ is a $T \times 1$ vector containing measurement error in the physical climate risk factor $\boldsymbol{g}$, d is the intercept, $\boldsymbol{\chi}$ is a $K \times 1$ vector of estimated exposure to each priced factor in the $K \times T$ matrix $\boldsymbol{\Omega}$, and $\boldsymbol{\epsilon}$ is a $T \times 1$ vector containing the error term. A significant association provides evidence that $\mathrm{Cov}(\boldsymbol{\zeta}, \boldsymbol{\Omega}) \neq 0$ and the unpriced portion should not be ignored by agents.

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

The primary aim of the three-pass procedure of Giglio and Xiu (2021) is to control for omitted factors and measurement error when identifying *priced* risk factors. This is because "while unpriced common factors may be interesting in their own right, they are not likely to be central puzzles in the intersection of macroeconomics and finance" (Clarke; 2022, p.161)[16]. In this paper, however, the aim is not to identify *which* factors are priced, which is admittedly a large motivation of the asset-pricing literature, but to what *extent* physical climate risk is priced. Instead of seeing measurement error $\boldsymbol{\zeta}$ as an error in the econometrician's measurement of the candidate risk factor $\boldsymbol{g}$, we test if it arises via error from agents when they price physical climate risk. This is a plausible alternative interpretation if and only if errors are co-vary with priced factors.

The unpriced sources of common variation can be empirically identified to understand what drives the errors:

$$\boldsymbol{\zeta} = h + \boldsymbol{\delta}'\boldsymbol{P} + \boldsymbol{\epsilon}, \quad i.i.d.\ \boldsymbol{\epsilon} \sim \mathcal{N}(0,1), \tag{21}$$

$\boldsymbol{\zeta}$ is a $T \times 1$ vector containing measurement error in the physical climate risk factor $\boldsymbol{g}$, h is the intercept, $\boldsymbol{\delta}$ is a $\rho \times 1$ vector of the estimated loadings, $\boldsymbol{P}$ is a $\rho \times T$ matrix of the candidate sources of common variation, and $\boldsymbol{\epsilon}$ is a $T \times 1$ vector containing the error term. We consequently 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.

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 errors in physical climate risk provides reasonable evidence that innovations in physical climate risk are driven by priced variation (the risk premium associated with physical climate risk) - but also unpriced variation arising from the five factors. For example, whilst not assessing unpriced variation specifically, Pástor et al. (2021) find that an ESG factor is associated with the value factor.

The second candidate source are industry returns. Even well established factors, such as the value factor,

[16]For example, the three-pass procedure finds no significant premia for the "pure-noise" factors given by Novy-Marx (2014), sunspots and a regime of recurring climatic fluctuations, but does so for theoretically-motivated factors such as market risk.

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).

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.; 2021; 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 wildfires and droughts. Consequently, the following model is estimated:

$$\boldsymbol{\zeta} = h + \boldsymbol{\delta}' \, log(\boldsymbol{P} + 1) + \boldsymbol{\epsilon}, \quad i.i.d. \; \boldsymbol{\epsilon} \sim \mathcal{N}(0, 1), \tag{22}$$

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 a robust estimate of its 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 we 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 and Xiu (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. We 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. We 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. We 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 a specified sample period 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[17].

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)[18]. 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

[17] This is a conservative approach. In a research report with *Four twenty-Seven*, DWS assume agents could have collected the data when *Four Twenty-Seven* were founded in 2012. The report on measuring physical climate risk in equity portfolios is available at: http://427mt.com/wp-content/uploads/2017/11/Measuring-Physical-Climate-Risk-White-Paper_Four-Twenty-Seven-2017.pdf

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

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 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[19]. 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)[20].

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[21]. 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 $\boldsymbol{R}$[22]. Ten value-weighted industry portfolios are also collected[23]. These are Consumer Non-Durables, Consumer Durables, Manufacturing, Energy, High Technology, Telecommunications, Shopping, Healthcare, Utilities, and Other.

[19] 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.

[20] In similar studies, Pástor et al. (2021) 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 (2021) drop stocks with market equity < NYSE 30th percentile and a closing price < \$1.

[21] Available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_5_factors_2x3.html.

[22] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/32_ports_me_beme_op.html.

[23] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_10_ind_port.html.

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)[24]. 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[25]. This data includes the estimated damages from each event as well as a short description about the nature of the disaster. Disasters 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.

[24] Available at https://www.ncdc.noaa.gov/billions/time-series.
[25] Available at https://www.ncdc.noaa.gov/billions/events/US/2010-2019.

5 Results

This section provides the results for the estimation of physical climate risk premia. We 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 excess returns of 0.70% and 0.06%, respectively. The *HEAT* and *RAIN* factors have negative average monthly excess returns of -1.16% and -0.78%, respectively. The correlation between the physical climate risk factors does not exceed 50% (untabulated). 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 excess return of 1.13% across the sample period. Figure 2 then shows the cumulative 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[26].

The performance of the physical climate risk factors during severe weather events and quiet periods is then studied to understand their temporal dynamics. To define these periods, Figure 5 in the Appendix shows a period of low damages from disasters that spans 2013 to 2016. Conversely, peaks in disaster damages can be seen in 2012 (150 billion dollars, CPI-adjusted) and 2017 (350 billion dollars, CPI-adjusted). Figure 6 in the Appendix then plots the cumulative performance of the *WIND* factor during two severe hurricane seasons in 2012 and 2017, and the cumulative performance of the *HEAT* factor during two severe wildfire seasons in 2017 and 2018. The cumulative returns of the *WIND* factor is shown to be positive prior to each hurricane season, drop during the hurricane season, and then recover afterwards. Similarly, the cumulative performance of the *HEAT* factor is shown to be positive prior to each severe wildfire, drop during wildfire season, and then recover afterwards. Figure 7 in the Appendix plots the cumulative performance of the *SEA* and *RAIN* factors during severe flooding in Thailand that impacted global semiconductor supply-chains. The cumulative return of the *SEA* factor is shown to be positive prior to the severe flooding and drops during the flooding. The performance of the *RAIN* factor is shown to underperform during October when the flooding was at its peak, but otherwise remains flat. These results provide indicative evidence that the

[26]The CAPM and five-factor performance of the physical climate risk factors are shown in the Appendix (Table 10 and Table 11).

factors capture some innovations in severe weather events. Quiet periods are then assessed in the lower panel of Figure 7 in the Appendix. The cumulative returns of the *SEA* and *WIND* factors are shown to be positive during this period. However, even during a quiet period, the cumulative returns of the *HEAT* and *RAIN* factors are negative, which runs counter to the theoretical approach posited earlier that the expected performance of the risk factors is positive.

Our attention now turns to estimating risk premia. Table 3 report the main results following the three-pass procedure of Giglio and Xiu (2021). Column 2 reports the average monthly 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 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[27]. As a comparison, the estimated risk premia for the market, size, and value factors are 1.12%, -0.01%, and -0.28%, respectively (untabulated). 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 3). 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*.

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 4. Rows 2-6 show the R^2 for the Fama and French (2015) five-factors - our 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

[27] Risk premium estimates from the Fama and MacBeth (1973) two-pass procedure are reported in the Appendix Table 12. The results show that the sign of the *WIND* and *HEAT* factors are the same as the Giglio and Xiu (2021) three-pass procedure.

HEAT factor, and 17% of the *RAIN* factor can be explained by the 7 latent factors[28]. Figure 3 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 4 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)[29].

The standard approach in the asset-pricing literature views these pricing errors as noise (classical measurement error). The attention now turns to testing this empirically. The errors can be viewed as errors made by agents (unpriced risk) if they are correlated with priced latent factors (Daniel et al.; 2020). Table 5 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. In untabulated results, errors in the investment factor (*CMA*) are the only errors from the Fama and French (2015) five-factors that are significantly associated with the priced latent factors, thus confirming that this result is predominantly unique to the physical climate risk factors. Consequently, we provide indicative evidence that noise in the physical climate risk factors can be thought of as mispricing rather than being driven purely by classical measurement error.

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 total wealth through their (unwilling) exposure to priced risks. Table 6 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

[28] Figure 9 in the Appendix visualises the R^2 values.

[29] Figure 10 in the Appendix plots the difference between the realised factor performance and the priced factor performance (i.e, the error).

(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 7 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 8 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 8 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 8 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%[30]. 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 in physical climate risk factor innovations.

[30]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.

6 Discussion and 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, this paper constructs 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 after controlling for omitted variable bias and measurement error.

We 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. Both exposure to sea-level rise and exposure to extreme rainfall are not priced as systematic risk factors. These results are consistent with the notion that for major salient risks, such as hurricanes, agents are compensated with higher returns, confirming evidence from Braun et al. (2021), Kruttli et al. (2021), and Addoum et al. (2021). Panel A and Panel C in Figure 1 demonstrate how the increased sentiment and uncertainty about these events can lead to outperformance for the *WIND* factor - there is an overreaction due to the dis-utility associated with severe weather which subsequently leads to higher returns afterwards (Alok et al.; 2020).

For the heat stress factor, *HEAT*, the results in this paper provide support for persistent mispricing of exposure, as evidenced by Pankratz et al. (2021) and Hong et al. (2019). Panel B in Figure 1 show how this phenomenon occurs: agents react negatively to the severe weather event but then forget about exposure by the time the next event occurs. The cumulative return to a factor under such dynamics are consequently biased downwards. The *HEAT* factor constructed in this paper consistently provides negative returns, even during quiet periods, confirming these dynamics. The paper stops short of answering convincingly why some physical climate risks, such as hurricane risk, command a positive premium, why others, such as heat stress, command a negative premium, and why others, such as sea-level rise and extreme rainfall, command no significant premium. This would be a fruitful area for further research.

An important novelty is viewing, under certain conditions, measurement error not as an error by the econometrician (classical measurement error), but by agents when pricing physical climate risk (non-classical measurement error). With this interpretation, we provide suggestive evidence that physical climate risk is priced with error compared to other known risk factors such as market risk. The errors in the physical climate risk factors are significantly associated with *priced* latent factors, confirming that some portion of the physical climate risk factors are unpriced by agents rather than being pure noise. 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 the alternative interpretation of the Giglio and Xiu (2021) three-pass procedure posited in this paper, since it provides one approach to disentangle the signal-to-noise ratio of physical climate risk (see Berg et al.; 2021 for an alternative approach). 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. Interesting future work may also wish to replicate the approach in other markets.

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Tables

Table 1: Summary Statistics: Financial Data

Variable	N	mean	median	SD	min	max
Excess return (%)	479	1.33	1.31	8.06	-53.39	81.51
Market equity (b)	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). b stands for billion.

Table 2: Factor Performance

Factor	*obs*	mean	t	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 (%)	119	1.13	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: Giglio and Xiu (2021) Three-Pass Regressions

	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: Average returns $\bar{\boldsymbol{g}}$ are excess returns. Robust t-statistics in parentheses.
Number of latent factors is chosen after inspecting the scree plot (Appendix, Figure 8).

Table 4: Variation of the Observed Factor Explained by Latent Factors

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

Note: R^2 proxies for the variation in physical climate risk $\boldsymbol{g}$ that is priced.
Number of latent factors is chosen after inspecting the scree plot (Appendix, Figure 8).

Table 5: Relationship Between Physical Climate Risk Measurement Error and Priced Latent Factors

Latent factors	*SEA* (ζ_{SEA})	*WIND* (ζ_{WIND})	*HEAT* (ζ_{HEAT})	*RAIN* (ζ_{RAIN})
Alpha	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
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 6: Relationship Between Physical Climate Risk Measurement Error and the Fama and French (2015) Five Factors

Factor	*SEA* (ζ_{SEA})	*WIND* (ζ_{WIND})	*HEAT* (ζ_{HEAT})	*RAIN* (ζ_{RAIN})
Alpha	-0.18	-0.21	0.32	-0.23
	(-1.39)	(-1.86)	(2.13)	(-2.90)
MKT-RF	0.09	0.12	-0.27	0.21
	(2.21)	(4.08)	(-5.42)	(10.64)
SMB	-0.05	-0.07	0.09	-0.17
	(-0.72)	(-1.14)	(1.31)	(-3.45)
HML	-0.59	-0.27	0.40	0.28
	(-6.51)	(-5.35)	(4.99)	(5.54)
RMW	-0.27	0.01	0.55	0.29
	(-2.71)	(0.20)	(5.51)	(4.83)
CMA	-0.28	0.53	0.15	0.32
	(-2.17)	(6.60)	(1.24)	(4.61)
R^2	0.55	0.28	0.52	0.66

Note: Robust t-statistics in parentheses.

Table 7: Relationship Between Physical Climate Risk Measurement Error and Industry Factors

Industry	*SEA* (ζ_{SEA})	*WIND* (ζ_{WIND})	*HEAT* (ζ_{HEAT})	*RAIN* (ζ_{RAIN})
Alpha	-0.21	-0.18	0.44	-0.20
	(-1.14)	(-1.42)	(2.56)	(-1.80)
Non-Durables	0.00	0.04	-0.02	0.09
	(0.01)	(0.69)	(-0.18)	(1.44)
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 8: Relationship Between Physical Climate Risk Measurement Error and Damages from the Realisation of Severe Storms and Tropical Cyclones

Panel A				
Event Damages	*SEA* (ζ_{SEA})	*WIND* (ζ_{WIND})	*HEAT* (ζ_{HEAT})	*RAIN* (ζ_{RAIN})
Alpha	-0.11	0.25	0.11	0.35
	(-0.34)	(1.70)	(0.40)	(2.19)
Severe Storm	0.03	-0.08	-0.04	-0.11
	(0.58)	(-2.75)	(-0.71)	(-3.79)
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	0.24	0.32	-0.25	0.26
	(0.76)	(1.86)	(-0.85)	(1.35)
Severe Storm & Tropical Cyclone	-0.06	-0.08	0.06	-0.07
	(-1.22)	(-4.10)	(1.27)	(-1.66)
R^2	0.00	0.07	0.01	0.03

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

Table 9: Relationship Between Physical Climate Risk Measurement Error and Damages from the Realisation of Flooding and Tropical Cyclones

Event Damages	*SEA* (ζ_{SEA})	*WIND* (ζ_{WIND})	*HEAT* (ζ_{HEAT})	*RAIN* (ζ_{RAIN})
Alpha	0.23	0.07	-0.15	-0.11
	(1.11)	(0.50)	(-0.67)	(-0.83)
Flooding & Tropical Cyclone	-0.14	-0.04	0.09	0.07
	(-2.05)	(-1.44)	(1.12)	(1.65)
R^2	0.04	0.01	0.01	0.01

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

Figures

Figure 1: Drivers of Climate Sensitivity

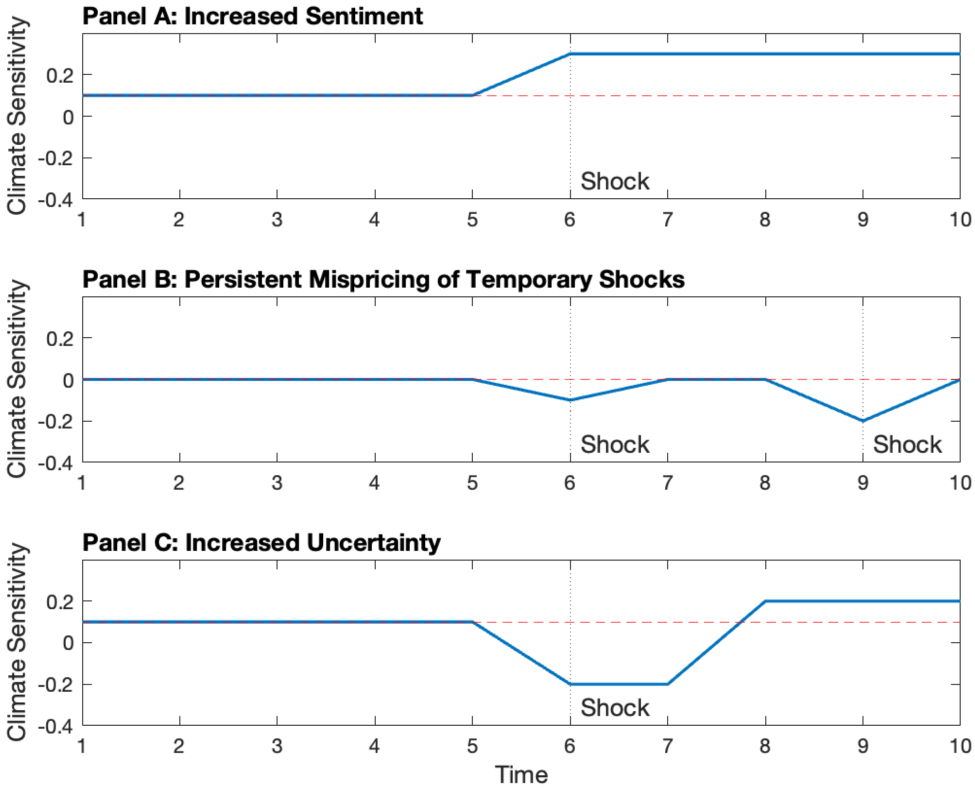


Figure 2: Cumulative Raw Performance of the Physical Climate Risk Factors

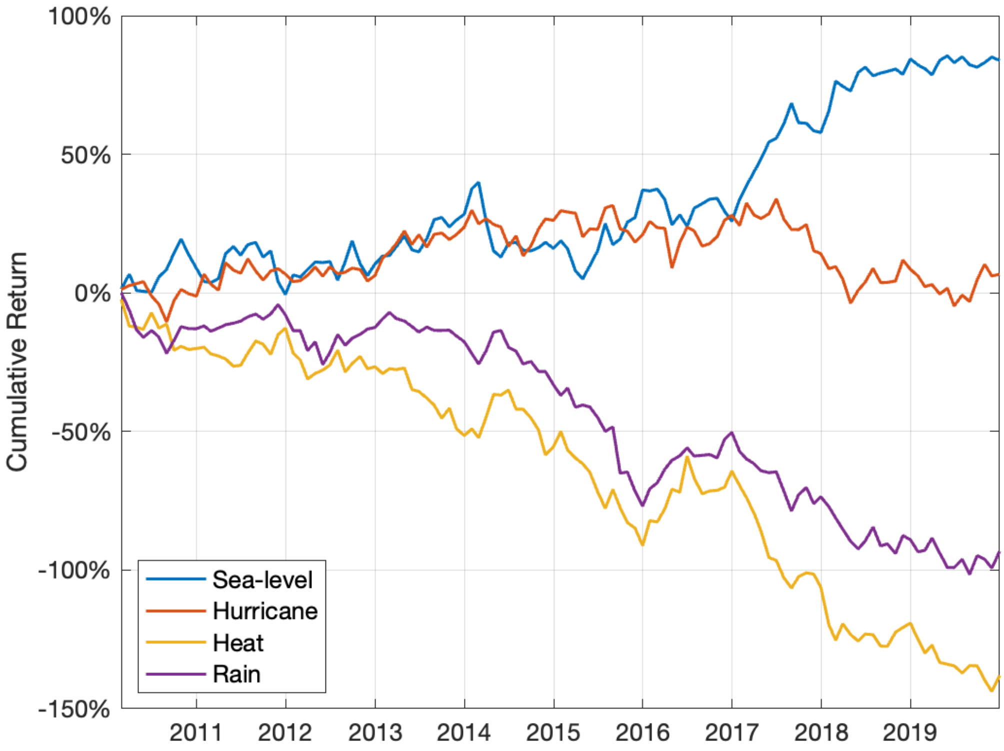


Figure 3: Factor Performance With and Without Error

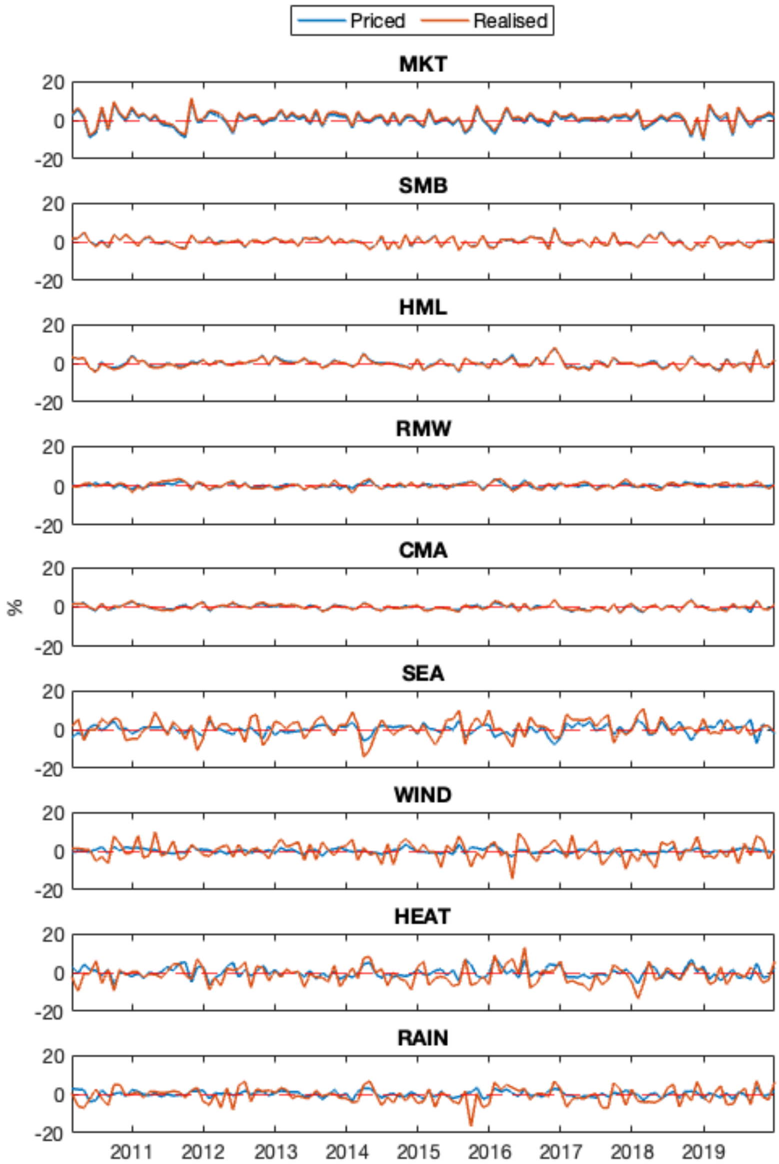
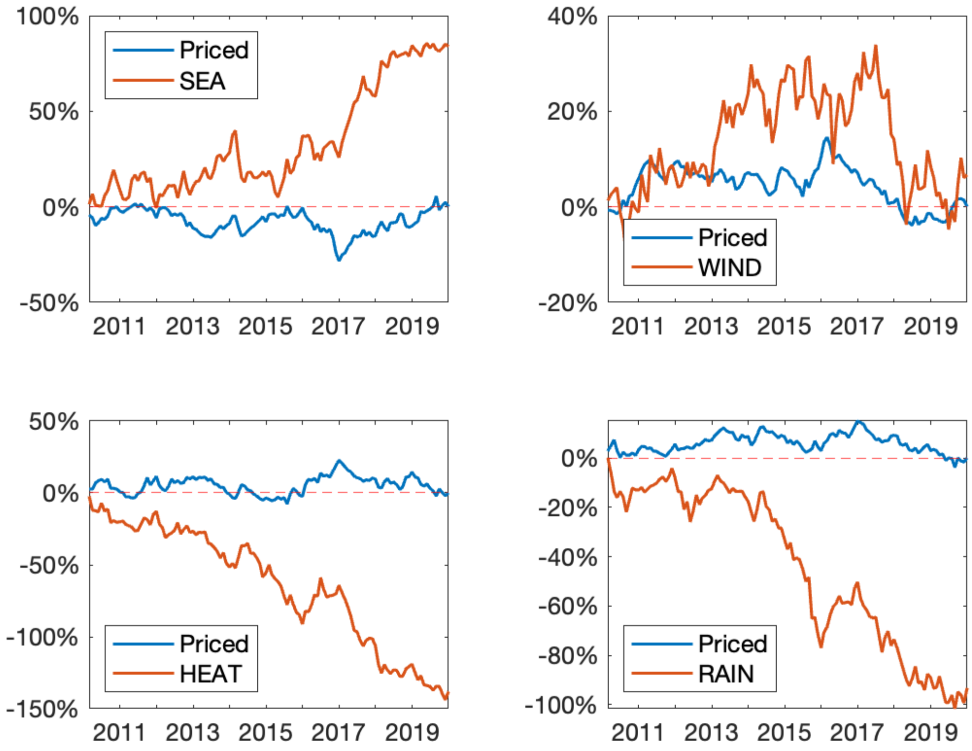


Figure 4: Cumulative Physical Climate Risk Factors With and Without Error



Appendix

A: 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, firm-level ISIN codes from *Four Twenty-Seven* are taken and converted to CUSIP codes[31]. Using the CUSIP codes, geographical and operating segment information is collected 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, the segment identifiers are concatenated 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.

[31] 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.

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

$$J_{it}(\boldsymbol{s^t}, \boldsymbol{s^b}) = \frac{\boldsymbol{s^t} \cap \boldsymbol{s^b}}{\boldsymbol{s^t} \cup \boldsymbol{s^b}}, \tag{23}$$

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%.

B: Expected Returns in a Two-Factor Model

This section shows, step-by-step, how the the two-factor sustainable asset-pricing model of Pástor et al. (2020) relates to the approach adopted in this paper. For convenience, the ESG taste term (Pástor et al.; 2020, Eq. 9) is dropped for clarity and the focus placed instead on the CAPM term and climate risk. To stay consistent with the notation used in Pástor et al. (2020), μ is used to denote expected excess returns.

In Pástor et al. (2020), expected excess returns are given as:

$$\mu = \mu_m \beta_m + c(1 - \rho_{mC}^2)\psi, \tag{24}$$

where μ are expected excess returns, μ_m is the market risk premium, β_m is exposure to the market, c is climate sensitivity, ρ_{mC} is the correlation between the unexpected market return ϵ_m and the stability of the climate $\tilde{C}$, and ψ is exposure to physical climate risk.

Pástor et al. (2020) give ψ as a $N \times 1$ vector of climate betas estimated as slope coefficients of unexpected stock returns $\tilde{\epsilon}$ on unexpected market returns ϵ_m and the stability of the climate $\tilde{C}$. In the framework posited in this paper, this term is simply asset j's exposure to physical climate risk estimated as slope coefficients of asset returns $\boldsymbol{r_j}$ on the physical climate risk factor $\boldsymbol{g}$ (i.e, loadings are not estimated after controlling for market returns). This is because the three-pass procedure of Giglio and Xiu (2021) does not require other risk factors such as market risk to be specified. The term ψ in Eq. 24 is then given as β_j.

In a similar fashion, the term $(1 - \rho_{mC}^2)$ in Eq. 24 is a multiplier representing the fraction of unexpected market returns e_m that can be explained by the stability of the climate. If this term is large (the correlation is large), then a large fraction of unexpected market returns can be explained by the climate $\tilde{C}$. The overall multiplier term will then be small and the physical climate risk term is smaller. This captures the idea that the market risk premium internalises physical climate risk. However, if the multiplier term is small (the correlation is small), then a small fraction of unexpected market returns can be explained by the climate $\tilde{C}$. Physical climate risk is therefore orthogonal to the market and is an independent risk factor.

We assume that the multiplier term equals zero: $(1-\rho_{mC}^2)=0$. This is reasonable because, even if CAPM regressions show that market risk is correlated with the climate, the estimated risk premium will be unbiased as long as the three-pass procedure of Giglio and Xiu (2021) is used. The CAPM term in Eq. 24 is thus dropped for brevity since risk premia can be estimated without having to specify the true asset-pricing model.

Given this information, Eq. 24 is simplified to the following:

$$\mu = \mu_m \beta_m + c\psi, \tag{25}$$

since $(1-\rho_{mC}^2)=0$. This is further simplified to:

$$\mu = \beta_j \boldsymbol{g}, \tag{26}$$

since $\mu_m\beta_m = 0$, $c = \beta_j$, and $\psi = \boldsymbol{g}$. Expected excess returns depend on asset j's exposure β_j to physical climate risk $\boldsymbol{g}$, which is the approach adopted in this paper.

Supplementary Tables

Table 10: CAPM Performance

	SEA	*WIND*	*HEAT*	*RAIN*
Alpha	0.59	-0.02	-0.62	-0.97
	(1.35)	(-0.06)	(-1.51)	(-2.55)
MKT-RF	0.10	0.07	-0.48	0.16
	(-1.02)	(0.61)	(-6.43)	(1.93)
R^2	0.01	0.00	0.14	0.02

Note: Robust t-statistics in parentheses.

Table 11: 5-Factor Performance

	SEA	*WIND*	*HEAT*	*RAIN*
Alpha	0.54	-0.11	-0.63	-1.11
	(1.43)	(-0.34)	(-1.77)	(-3.19)
MKT-RF	0.11	0.11	-0.46	0.26
	(0.83)	(0.89)	(-4.58)	(2.74)
SMB	-0.18	-0.03	0.12	-0.15
	(-1.07)	(-0.19)	(0.65)	(-0.79)
HML	-0.65	-0.14	0.30	0.19
	(-2.31)	(-0.58)	(1.19)	(0.96)
RMW	-0.65	0.10	0.40	0.45
	(-1.99)	(0.29)	(1.78)	(1.67)
CMA	-0.72	0.37	0.78	0.71
	(-1.91)	(1.14)	(1.96)	(2.62)
R^2	0.25	-0.03	0.25	0.13

Note: Robust t-statistics in parentheses.

Table 12: Fama and MacBeth (1973) Two-Pass Regressions

	(1)	(2)	(3)	(4)
MKT-RF	1.12	1.15	1.15	1.15
	(3.28)	(3.35)	(3.35)	(3.35)
SMB	0.02	0.00	0.00	0.00
	(0.10)	(-0.02)	(-0.02)	(-0.02)
HML	-0.30	-0.31	-0.31	-0.31
	(-1.42)	(-1.44)	(-1.46)	(-1.46)
RMW	0.21	0.29	0.27	0.29
	(1.03)	(1.31)	1.27	(1.33)
CMA	-0.16	-0.09	-0.13	-0.11
	(-0.71)	(-0.42)	(-0.58)	(-0.52)
SEA	-0.81			
	(-1.16)			
WIND		0.22		
		(0.34)		
HEAT			-0.14	
			(-0.26)	
RAIN				0.29
				(0.61)
R^2	0.63	0.58	0.57	0.57

Note: Robust t-statistics in parentheses.

Supplementary Figures

Figure 5: US Billion Dollar Severe Weather Events identified by the National Oceanic & Atmospheric Administration (NOAA)

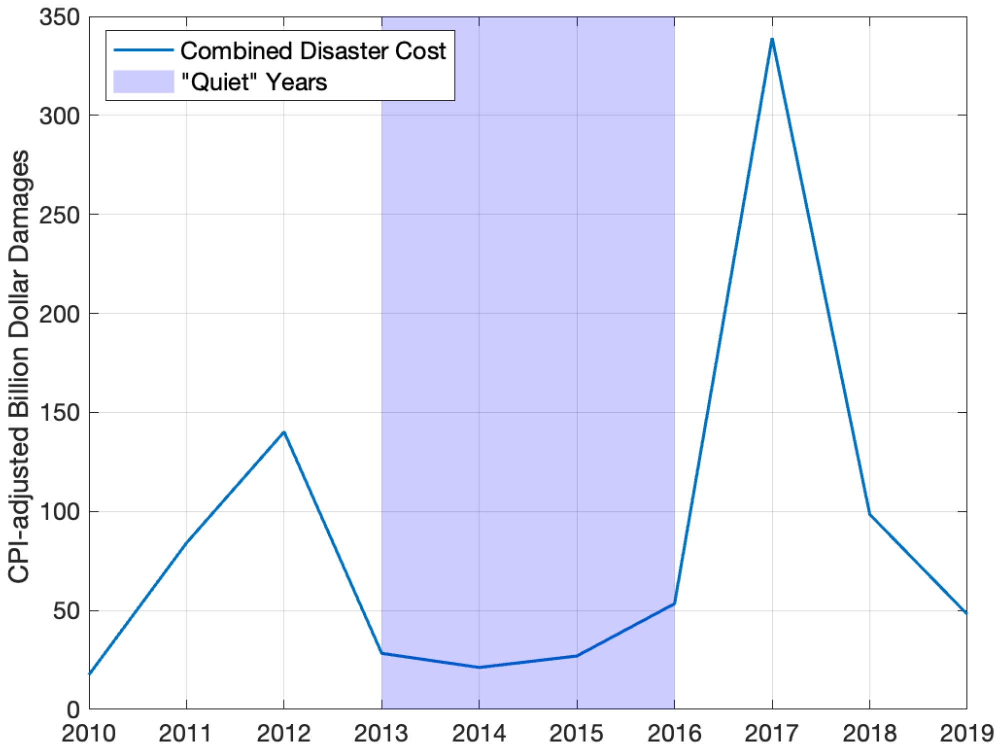


Figure 6: Cumulative Factor Performance for Hurricane Risk and Heat Stress During Severe Events

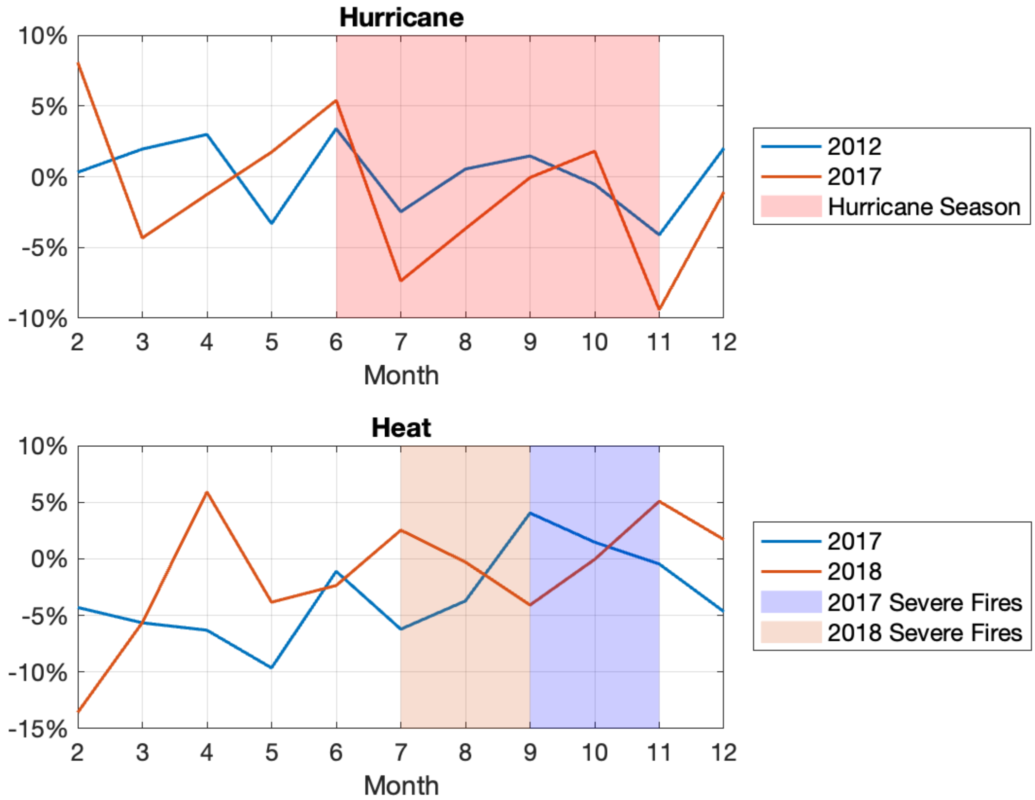


Figure 7: Cumulative Factor Performance During Severe Floods and Quiet Periods

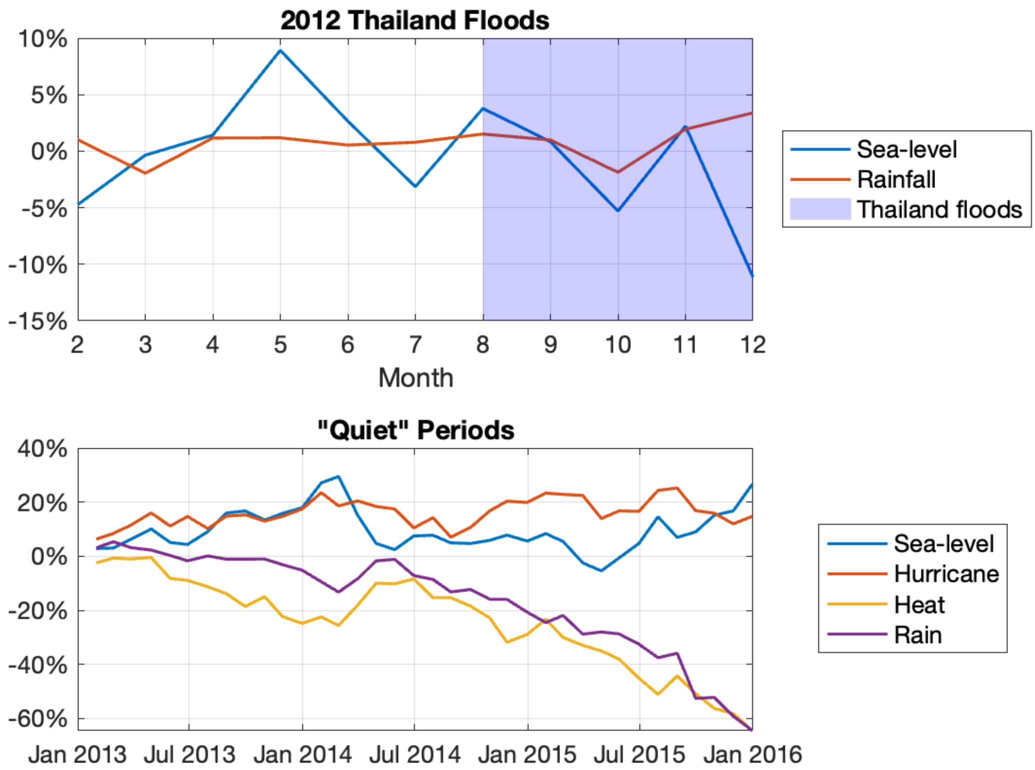


Figure 8: Logarithm of the First 15 Eigenvalues of the Covariance Matrix of 32 Portfolios Sorted on Size, Book-to-Market, and Investment

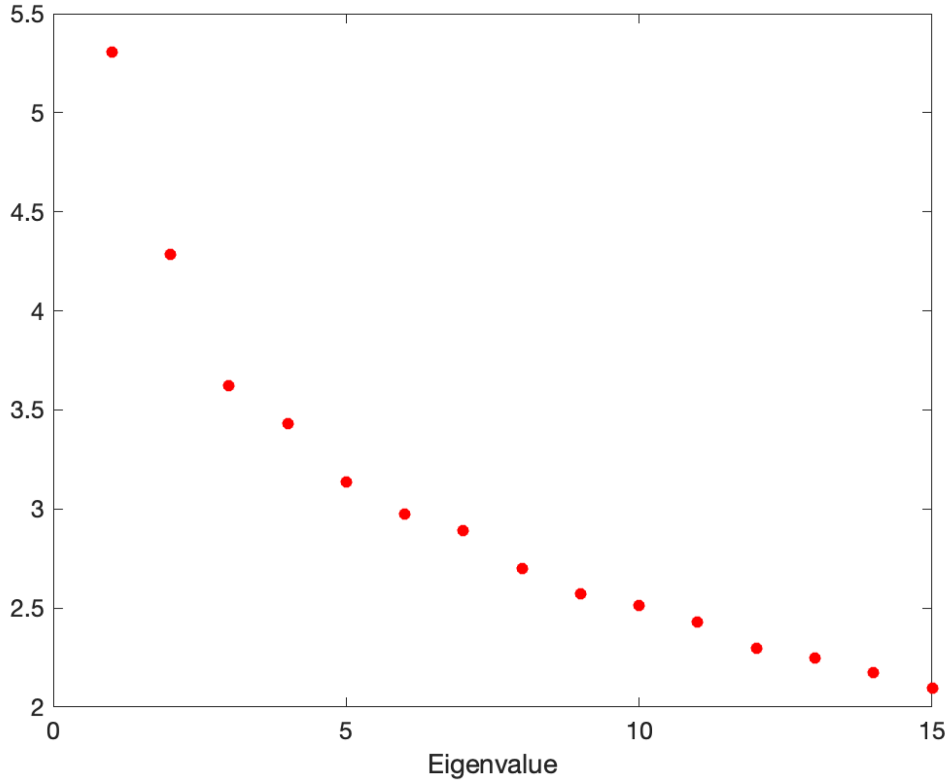
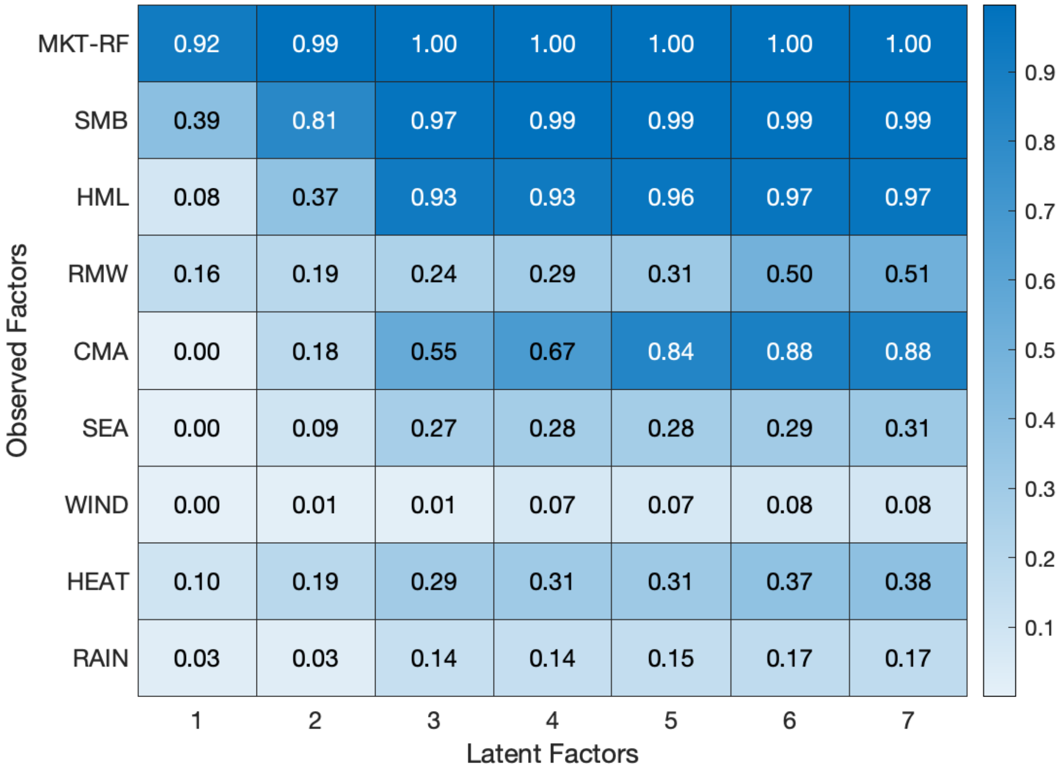


Figure 9: Priced Portion of Observed Factors - Proxied by R^2



Number of latent factors is chosen after inspecting the scree plot (Appendix, Figure 8).

Figure 10: Cumulative Difference Between the Realised and Priced Portion of Each Physical Climate Risk Factor