Pricing Climate Risk

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ABSTRACT

I exploit a new dataset from *Four Twenty Seven* and identify physical climate risk factors that can explain the variation in global individual stock returns. North American stocks are currently exposed to an extreme rainfall factor and an overall climate risk factor. European and Japanese stocks are currently exposed to an extreme rainfall factor, a heat stress factor, and an overall climate risk factor. I assess the pricing of policy related to these risks by drawing on new data from the Transition Pathway Initiative that summarises publicly-available information on a firm's emissions and targets. Physical climate risk and transition risk factors cannot explain the returns of portfolios sorted on standard accounting variables (such as investment, momentum and profitability), and vice-versa. However, a quality factor can explain both climate-related and non-climate-related portfolios. Climate risks may be mispriced and quality captures a confounding association between the environment and the zoo of factors used to explain asset returns.

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Using firm level physical risk data, I estimate the market pricing of climate-related risks. Firms are ranked on their physical risk exposure and regressed onto environmental and non-environmental factors. To do so, I utilise a new asset-level dataset from *Four Twenty Seven*, a climate data firm, to measure exposure through a firm's operations, supply-chain, and market risk. A long-short strategy that uses the signal for operational extreme rainfall exposure yields a ten year return of 25.83% whilst a long-short strategy using a signal for operational heat stress yields a ten year return of 77.10%. I focus on extreme rainfall and heat stress since, out of the *Four Twenty Seven* data, they cover historical exposure and allow me to utilise a panel dataset. I conclude that mispricing of physical risks may be present in markets.

To validate the approach, I test whether adding physical risk portfolios to a four factor asset pricing model yields more explanatory power. My results show that they do, but only for the extremely high risk and low risk portfolios. I then turn to geographically specific portfolios. I find that an extreme rainfall factor and an overall physical risk factor are significant for returns for North American stocks. The returns on European and Japanese stocks can be explained by extreme rainfall, heat stress, and an overall physical risk factor.

Expanding the physical risk factors to a large validation set, I regress the physical risk factors onto individual firm returns and find it improves model fit. The physical risk factors are statistically significant at the 1% level for 14% of the sampled firms, compared to 10% to 12% for the size, value, and momentum factors, respectively. The market factor dominates the model with 34% of firms loading significantly onto it.

I also test the pricing of climate-related policy risks. Firms are sorted on their annual net carbon dioxide emissions and on whether they have an emissions reduction target. A similar approach sorts firms on carbon dioxide emissions and whether their target is compliant with the Paris Agreement. I call these transition risk factors and the set of transition and physical risk factors are known as environment factors.

I then utilise a double-selection Least Absolute Shrinkage and Selection Operator (LASSO) approach with various factors identified in the literature to penalise unimportant factors in a high-dimensional space. I regress double-sorted portfolios onto these factors and identify those able to explain various characteristics of asset returns. Interestingly, I find the environmental[1] factors cannot explain the returns of the non-environmental portfolios, and vice-versa, after imposing a penalty on the model that rewards scarcity (i.e. a small number of explanatory variables). This shrinks uninformative covariates to zero using the LASSO approach. However, the quality factor spans both environmental and non-environmental portfolios, implying an association between the quality factor and environmental risk.

Finally, I compare *Four Twenty Seven*'s physical risk scores to the market pricing of these risks as measured by the average loading on the physical risk factors. Japanese and European stocks are found to be more efficiently priced in terms of physical risk exposure compared to stocks headquarted in the U.S and China.

This work contributes to a growing literature on asset prices and climate-related factors. To my knowledge, I am the first to utilise a new dataset that uses asset-level data on a global level when assessing physical risks. My physical risk measure is a single firm-level score for equities covered by *Four Twenty Seven*. Addoum, Ng, and Ortiz-Bobea (2019) assess temperature shocks but their sample is limited to the border of the United States. Others make assumptions about which firms are affected (Pankratz, Bauer, and Derwall, 2019; Hong, Li, and Xu, 2019) or avoid dealing with asset-level data (Kumar, Xin, and Zhang, 2019).

This work also relates to long-run climate risks. Bansal, Kiku, and Ochoa (2019) find temperature shocks produce an equity risk premium due to impacts on the aggregate economy (Deryugina and Hsiang, 2017; Burke, Hsiang, and Miguel, 2015). Engle III, Giglio, Kelly, Lee, and Stroebel (2019) attempt to hedge these risks by forming portfolios correlated to climate change news, whilst Andersson, Bolton, and Samama (2016) calculate a low-carbon equity index with a low tracking error to a traditional benchmark. de Jong and Nguyen (2016) conduct similar analysis for bonds. These risks are notoriously difficult to quantify (Kruttli, Roth Tran, and Watugala, 2019; Schlenker and Taylor, 2019), much like the explosion of characteristics identified in the factor zoo (Cochrane, 2011; Harvey, Liu, and Zhu, 2016; Feng, Giglio, and Xiu, 2019). I contribute to this debate by utilising one regularisation technique in the literature by Belloni, Chernozhukov, and Hansen (2014) and Feng et al. (2019). My findings suggest the environment is likely to be a confounding factor in the cross-section.

The paper also contributes to our understanding of transition risk; the risks and opportunities posed by the transition to low-carbon economies (Clapp, Lund, Aamaas, and Lannoo, 2017). I find transition risk factors are priced in the cross-section, much like Trinks, Scholtens, Mulder, and Dam (2018) and Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2019). I show how the market may be incomplete by not representing future climate-relevant states of nature (Rubinstein, 1975; Gollier, 2017).

Section I details the empirical approach, Section II discusses the data used for the work, and Section III provides the results.

I. Empirical Approach

A. *Factor-mimicking-portfolios*

Following Fama and French (1993), firms are double-sorted annually into value-weighted portfolios based on their size and physical risk. The monthly returns of these portfolios are calculated in excess of the risk-free rate. The risk factor-mimicking-portfolio equals

$$0.5(SH_t + BH_t) - 0.5(SL_t + BL_t), \tag{1}$$

where SH_t is the return of the small size and high physical risk portfolio, BH_t is the return of the big size and high physical risk portfolio, SL_t is the return of the small size and low physical risk portfolio, and BL_t is the return of the big size and low physical risk portfolio. Equation (1) is one of the explanatory variables in the model. The dependent variable is constructed by forming ten decile value-weighted portfolios that are annually sorted on physical risk. For example, portfolio 1 holds the lowest 10% of firms whilst portfolio 10 holds the highest 10% of firms. Using portfolios as the dependent variable provides more stable betas (Petersen, 2009), but I also resort to individual firms in further tests.

I construct six physical risk factor-mimicking-portfolios from the available data and two transition risk factors. They are a composite physical risk factor, 427_L, that is adjusted for land and double-sorted on size and physical risk. I adjust for land in order to backtest the *Four Twenty Seven* scores and explain this fully in the data section. The factor is long firms that are considered at high risk and short firms that are considered low risk. I create a physical risk factor, 427_I, that is adjusted for industry and uses *427*'s classification of best-in-class, average and worst-in-class. The factor is then long worst-in-class firms and short best-in-class firms. This is not adjusted for land. Another risk factor is constructed that simply uses the *427* model without adjusting for land — known as 427_U. I create a physical risk factor that captures heat stress, *HOT*, by using the *427* heat stress score and adjusting for land in order to extend the time horizon. I create a similar factor that captures historical extreme rainfall risk — known as *WET*. The factors are then long firms considered high risk and short firms considered low risk. I create a transition risk factor that captures carbon risk, $CO2_T$, and sorts firms on their historical net CO_2 emissions, standardised by net sales so to not penalise large firms, and whether they have an emissions reduction target. The factor is long firms in the highest emissions decile with no target and short firms in the lowest emissions decile with an emissions target. This captures the current and future preparedness of firms in the low-carbon transition. I also create a transition risk factor that captures carbon risk, $CO2_P$, and sorts firms on their historical CO_2 emissions, standardised by net sales, and whether their emissions target is above or below the Paris Agreement. This captures the preparedness of firms for the low-carbon transition but actually measures their targets in line with international goals — an improvement on the previous factor and on Görgen et al. (2019).

B. Models

B.1. Testing the factors

I first regress the ten decile portfolios sorted on physical risk on the Carhart (1997) four-factor model. Let R_{it} denote a vector of excess returns of ten value-weighted portfolios i sorted on physical risk in month t. MKT_t is the market factor, SMB_t the small-minus-big size factor, HML_t the high-minus-low value factor, and WML_t the winners-minus-losers momentum factor. I add to these controls the physical risk factors. $427_{L,t}$ is the total physical risk factor (eq. 2), WET_t is the extreme rainfall risk factor (eq. 3), and HOT_t is the heat stress risk factor (eq. 4). The same models are also estimated for geographically specific regions.

$$R_{it} = \alpha + \beta_i MKT_t + \beta_i SMB_t + \beta_i HML_t + \beta_i WML_t + \beta_i 427_{L,t} + \epsilon_{it}, \tag{2}$$

$$R_{it} = \alpha + \beta_i MKT_t + \beta_i SMB_t + \beta_i HML_t + \beta_i WML_t + \beta_i WET_t + \epsilon_{it}, \tag{3}$$

$$R_{it} = \alpha + \beta_i MKT_t + \beta_i SMB_t + \beta_i HML_t + \beta_i WML_t + \beta_i HOT_t + \epsilon_{it}. \tag{4}$$

I replicate the same models but change the dependent variable, R_{it}, to individual stock returns instead of decile portfolios, running over 19,000 seperate regressions.

B.2. Taming the factors

I then follow Belloni et al. (2014) and Feng et al. (2019) and utilise a double-selection strategy to select meaningful covariates and guard against omitted variable bias. First, I estimate a model using LASSO on the market, size, value, momentum, betting-against-beta, quality-minus-junk, up-minus-down, physical risk, and transition risk factors, denoted by the vector X_t. R_{it} is a vector of portfolios i double-sorted on size and investment (6), size and momentum (6), size and profitability (6), size and value (6), size and physical risk (10), and size and transition risk (10) with the number of portfolios for each ranking given in brackets. In total, I run 94 separate regressions.

$$R_{it} = \alpha + \beta_i X_t + \epsilon_{it} \tag{5}$$

The first step searches for factors that can explain the cross-section. The second step then examines the factors to see if omitting any would lead to omitted variable bias, minimising the ex-ante model selection bias in the process [2]. As an example, for the largest size and investment portfolio, the first stage selects the market, size, value, quality, and rainfall factors as being significant at the 10% level for explaining portfolio returns with an R^2 of 97%. The second step reduces this to just the market factor.

II. Data

A. Financial data

For the training sample, monthly returns of global equities are sourced from *Datastream* and trimmed as standard in the literature (Ince and Porter, 2006), such as winsorizing at the 1% level and removing missing observations. I remove financial service firms in the training sample but not the validation sample. The risk-free rate, monthly common risk factors, and sorted portfolios are sourced from Ken French's data library. Other factors, used in Frazzini and Pedersen (2014), are taken from the *AQR Capital Management* website. Emerging market factors come from Stefano Marmi's website. Net sales and market equity are from *Datastream*. For the validation sample, I download global individual stock returns for over 19,000 firms from *Compustat/CRSP*, of which 73.84% are U.S firms. I repeat the analysis without U.S firms (n = 7,162) and find similar results.

B. Environmental data

I use environmental data from *Four Twenty Seven*, *CDP*, *Datastream* and the *Transition Pathway Initiative* to construct the risk factors in the training sample. *Four Twenty Seven* is a leading provider of market intelligence on the impacts of climate change for firms and investors. By identifying the location of corporate production and retail sites around the world, their risk measure captures firm exposure by assessing operations risk, market risk, and supply-chain risk. 70 scoring points are allocated to operations risk, of which 5 points are allocated to socioeconomic risk and the other 65 are distributed evenly among heat stress, water stress, extreme rainfall, sea level rise, and hurricanes & typhoons. 7.5 points are allocated to a firm's country of sales and industry weather sensitivity, respectively, to capture market risk. 7.5 points are also allocated to a firm's country of origin of the likely supply-chain and sector resource demand, respectively. This information relies on climate models and projections, with varying time-horizons used to construct the scores. For example, heat stress and extreme rainfall use a baseline period of 1975-2005 and a projection up to 2020-2040[3]. CO_2 emissions and physical risk data from *CDP* are downloaded from *Datastream*. The *CDP* physical risk data asks firms whether they acknowledge they are exposed to physical risks.

C. Assumptions

Tests on market efficiency assume information is available to investors. The *Four Twenty Seven* scores have been created from 2012 to 2018 but are stationary, therefore posing a problem for a historical asset pricing model. To control for this, I use land data from *Datastream* which represents real estate held for productive use as a proxy for geographical expansion and contraction. Firms are kept in the dataset only if the amount of land they hold has changed by less than 5% from the 2017 value. This reduces the training sample to 668 firms for the period 2008 - 2017. For robustness, I compare the physical risk factor to physical risk data from *CDP*, where firms voluntarily disclose their exposure to physical risks. Furthermore, backtesting the *WET* and *HOT* factors seems more plausible since these measures use historical climate information and project further information into the future. This implies the firms in the sample fall within the set of probabilistic climate variation that is picked up by **?**'s physical risk score.

III. Results

A. Factors

Figure 3 shows descriptive statistics for the six physical risk factors that seek to explain the global variation in asset returns. Apart from 427_I and 427_U, all of the factors display a negative mean monthly return — a similar finding to Görgen et al. (2019). This implies that exposure to this factor, which mimics physical risk, leads to negative excess returns. Over the sample period the factors mostly display a negative cumulative return; meaning that exposure to extreme rainfall, for example, leads to negative returns. An investor could generate returns of 77% over the 10 year period by investing in low risk firms and selling high risk firms.

[Place Figure 3 about here]

Figure 4 plots the cumulative returns of the physical risk factors to visualise these findings. For example, 427_I and 427_U both seem to be outliers which suggests it is more robust to control for land change — the *CDP* factor provides confidence for this conclusion because no adjustment was required for this factor and it follows closely the adjusted factors in the expected manner.The *HOT* and *WET* factors show steadily declining trends during the sample period — a sign that the factor is capturing some long-run trend in risk.

[Place Figure 4 about here]

The correlation between the physical risk factors includes useful information as to their added value in an asset-pricing model (figure 5). For example, *WET*, *HOT* and 427_L all show small correlations to traditional factors; the market (*MKT*), size (*SMB*), value (*HML*), betting-against-beta (*BAB*) and up-minus-down (*UMD*). The correlations to the quality factor, *QMJ*, are somewhat higher but negative, circa 20%, which implies that physical risk is a quality issue. Quality firms, as defined by Frazzini and Pedersen (2014) as profit, payout, safety and growth, are not dissimilar from low risk firms. We can theorise this as the following. Quality firms tend to look after their immediate surroundings or relocate to sensible locations. As such, a low risk environment is a quality-enhancing feature (or vice-versa). I provide evidence for this. Between themselves, the factors are quite strongly correlated but the *HOT* and *WET* factors remain independent other than with respect to the 427_L factor. This seems plausible as the 427_L factor is the aggregate of the environmental subsets and these narrower factors capture some specific notion of the environment in which firms operate.

[Place Figure 5 about here]

B. Testing the factors around the world

The $\mathit{427}_U$, $\mathit{427}_I$ and *CDP* factors are dropped at this stage in order to focus on the remaining physical risk factors. This seems sensible since the *CDP* factor is highly correlated to the other factors yet has a much smaller sample size, whilst the former two show implausible properties which is likely due to their unadjusted construction. However, it cannot be ruled out that in a simple 2017 cross-section they may have explanatory power. The paper does, however, assess the *CDP* factor as a robustness check (see appendix, figure 1).

Figure 6 shows the Fama and French (1993) and Carhart (1997) 4 factor (4F) model with the additional physical risk factor (5F). The simple 4F model is estimated first (but not shown) and then compared to the 5F model. The significance level of an f-test on nested models is then given on the Adj. R^2 5F row. The results show that adding the $\mathit{427}_L$ factor significantly enhances the 4F model for the low-risk (i.e. low physical risk score) deciles and the high-risk deciles. This supports the findings from Görgen et al. (2019) that physical and transition risk is priced in the extremes. The loadings on this risk factor also exhibit a plausible narrative. Low risk firms are negatively correlated to the factor whereas high risk firms are positively correlated.

[Place Figure 6 about here]

The *WET* (figure 7) and *HOT* (figure 8) factors also show a similar pattern. Middle deciles display no significance in explaining asset-returns whereas the low and high risk deciles can be explained by the factor, with the same signs as the $\mathit{427}_L$ loadings. Importantly, the intercept terms are also significant — implying the model is not able to explain the entire variation in returns from the five factor model.

[Place Figure 7 about here]

[Place Figure 8 about here]

A global common risk factor relies on assessing a global pool of firms. However, it is unlikely that physical risk is homogeneous across the world with different regions and biomes affecting firms heterogeneously. To expand on previous environmental asset pricing models (Hong et al., 2019; Görgen et al., 2019), I construct geographically specific factors that use regional risk factors from French (2018) and Marmi (2013) as well as altering the construction of the physical risk factors to only include geographically-specific firms. This includes North America, Europe, Japan, Asia Pacific, China, and Brazil. The results suggest that the global model hides regional differences.

For example, in North America, of the three physical risk factors, *WET* is more significant and can explain the low-risk decile through to the high-risk decile with a few exceptions (see appendix, figure 18). Europe is significantly priced for all of the three physical risk factors and shows an improvement from the global test terciles or the *WET* terciles (see appendix, figures 19, 20, and 21). Brazil, on the other hand, does not have any firms in the sample that are considered low-risk. Of the high-risk deciles, all of them are significantly priced but show a loading that decreases from low-to-high. This implies a fragmented association between firms and the risk factors.

C. *Applying the factors to individual firms*

The next step in the empirical approach of this paper is to test the trained factors on the full sample. The full sample consists of 19,665 firms from *CRSP/Compustat* which is available at *Wharton Research Data Service*. Firms classified as being incorporated in the U.S make up 73.84% of the sample which is much greater than the training sample. Consequently, the analysis is also conducted without firms from the U.S (leaving 7,62 unique firms). The dependent variable in these models changes from portfolios (Fama and French, 1993) to individual firms which solves one of the issues discussed in the literature. This is the idea that portfolios favour the asset-pricing model by making it more likely that the factor will explain a portfolio sorted on a variable used to construct the factor.

Monthly returns from the individual firms are regressed on the 5F model. Figure 9 shows the average adjusted R^2 from the four models and provides evidence that the 427_L and *WET* factors add explanatory power from the 4F model. The average R^2 for the *HOT* factor is 0.01% lower than the 4F model, indicating they are very close.

[Place Figure 9 about here]

Figure 10 shows the benchmark 4F model and the average β coefficients of the tested firms with the number of firms that are significant at the 5% and 1% level. The market factor is most significant across the assets using the French (2018) global risk factors. For the robustness check without U.S firms, the benchmark model stays statistically the same but the average R^2 increases to 0.15 (15%). The average β on the *WET* factor decreases dramatically to -0.46 compared to the full sample coefficient of -2.24. This could imply that U.S firms are more exposed to the *WET* factor. Interestingly, 1,039 of the firms have a significant loading for *WET*. The *HOT* factor robustness check is similar. The coefficients of the benchmark model remain the same and the *HOT* factor has a reduced β of -0.46 compared to -0.14 in the full sample. 1,083 firms have a significant loading on *HOT* (1,083 at the 1% level). The β on the 427_L risk factor increases by 0.1 compared to the full sample and is statistically significant at the 1% level for 1,027 firms.

[Place Figure 10 about here]

Of interest to this paper is the comparison between the benchmark model (figure 10) and the 427_L, *HOT* and *WET* factors. Run on the validation sample, the 427_L model (figure 11) implies that the 427_L factor has a significant, but small, negative loading on 2,663 firms (14% of the sample). The *HOT* (figure 34) and *WET* (figure 35) factors are also significant on 14% of the sample but have larger loadings (-.14 and -2.24, respectively). Figures 11, 34 and 35 therefore provide evidence that, out-of-sample, the physical risk factors still hold explanatory power in a similar proportion to Görgen et al. (2019).

[Place Figure 11 about here]

D. Taming the factors

When the true number of factors is low, an estimation of the price of risk leads to a clear interpretation of the marginal utility for factor exposure. However, in a high-dimensional space this becomes problematic. The LASSO technique can be used to select non-zero factors. Feng et al. (2019) propose a double-selection LASSO approach with the two-pass Fama-MacBeth method to estimate risk prices. This paper consequently takes advantage of code provided by Christian Hansen (Belloni et al., 2014) to run the first double-selection stage on the physical risk factors. The factors to be tested are the following: the market, size, value, momentum, betting-against-beta, quality-minus-junk, up-minus-down, 427_L, *WET*, *HOT*, 427_U, 427_I, *CDP* and two transition risk factors $CO2_T$ and $CO2_P$. Consequently, we can test what factors remain after the double-selection LASSO method. The overall framework can be considered one of imposing scarcity: extracting the most influential factors without any prior knowledge. Indeed, one should 'bet on scarcity' because these models perform better than dense ones (James, Witten, Hastie, and Tibshirani, 2013).

The Belloni et al. (2014) approach searches for factors that can explain the cross-section. The added benefit is that explaining the cross-section is considered more robust than explaining the time-series (Feng et al., 2019). The second step examines the factors to see if omitting any of them would lead to omitted variable bias (OVB), minimising the ex ante model-selection bias in the process. The paper tests this model on sorted portfolios. However, one major issue remains. The characteristics according to which the portfolios are sorted will create a favourable bias for the said attributes in the results. For example, a size and investment sorted dependent variable will result in a size and investment risk factor being selected as significant after the test (Harvey and Liu, 2018). A contribution of this paper is that it supports this conclusion.

Consider an example. For the largest portfolio sorted on size and investment, the first stage selects market, size, value, quality, and rainfall as being significant at the 10% level. The model selects the market factor as the only factor that can parsimoniously explain the returns, producing an R^2 of

97% after the second stage. This process is repeated for all of the aforementioned decile portfolios and summarised in figure 12.

[Place Figure 12 about here]

The physical risk factors cannot explain any cross-sectional variation for the non-environmental portfolios, with the market factor remaining consistently powerful. The quality factor, *QMJ*, can explain some of these portfolios — confirming our earlier intuition on the link between quality and physical risk. The other physical risk factors contrast previous tests. Whilst some factors do have explanatory power, the pattern is not uniform. However, the $CO2_P$ factor can significantly explain all of the environmental portfolios. This implies that a forward-looking transition risk factor is relevant for asset prices.

E. Market efficiency

Monthly returns from the training sample are regressed on the factors 427_L, *HOT* and *WET* to identify exposure through their beta's. Country averages are then taken. Consequently, we can assess how countries are exposed to, and to what extent prices reflect, physical risk. If the priced physical risk exposure differs from the *427* score then some mis-allocation may be present. Dietz, Bowen, Dixon, and Gradwell (2016) and Görgen et al. (2019) define a similar environmental β.

Figures 13, 14 and 15 show the comparison between physical risk exposure (β) and the *427* scores which rely on climate models. For each figure, panel (a) shows the asset-pricing exposure for each country whilst panel (b) shows the predicted physical risk. Consequently, we can visually assess how financial markets are pricing physical risk.

[Place Figure 13 about here]

For heat stress, South America seems relatively well priced. The analysis earlier implied that Brazil has large physical risk exposures and this is matched by the *427* scores. India, Japan and Europe are similarly well priced. Conversely, the U.S is not pricing its physical risk exposure. Some areas, such as Turkey and Australia, seem to be pricing risks that are not so severe. This could mean that the firms here and more global, as the analysis uses their location of incorporation, or the pricing of assets is led by other factors.

[Place Figure 14 about here]

For extreme rainfall, North and South America are similarly mispriced in terms of their pricing of physical risk. For areas such as Sweden, it is possible that behavioural trends in preferring responsible firms may be driving higher risk pricing but this is not proved empirically. Asia Pacific is also mispriced.

[Place Figure 15 about here]

IV. Limitations and Conclusion

This paper relies upon *427* physical scores which are the culmination of many climatic models and data-points. As such, the risk factors constructed are simplified into the *427* scores. The paper does not consider transaction costs of an investment strategy that utilises *427* data. These are important considerations within financial economics. To extend the Belloni et al. (2014) model, future work could follow the approach by Feng et al. (2019) using the Fama-MacBeth approach to estimate risk premia. Furthermore, a more convincing dependent variable is needed to test the factors. This paper uses individual firms and sorted portfolios but the results are highly dependent on what is used. A common factor model should be robust to these changes and consequently provokes future research into physical risks before the factor can be deemed universal. Future work could also explore the link between the quality factor and the environmental factors.

The novelty of the work comes from using the *427* data and by constructing physical risk factors — which has seldom been done in the literature. Although significant excess returns were found, an exploration into whether they are due to mispricing or compensation for risk would be useful because this explains the behaviour of these assets. This paper finds that proxies for overall physical risk, heat stress and extreme rainfall add to common factor models and explain the cross-section of returns. These results are robust to global and regional samples and multiple factor tests.

Appendix A.

Figure 1. *CDP* factor: Global decile portfolio performance

	Not Exposed	Exposed
Intercept	-1.388*	-1.248*
	(-2.58)	(-2.26)
MKT	0.386**	0.417**
	(3.19)	(3.36)
SMB	0.823*	0.945*
	(2.11)	(2.36)
HML	-0.510	-0.385
	(-1.56)	(-1.15)
WML	-0.160	-0.143
	(-0.97)	(-0.85)
CDP	-1.607***	0.201
	(-8.03)	(0.98)
Adjusted R^2	0.401	0.140

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 2. Variable Description

Variable	**Sample**	**Description**	**Source**
ISIN	training	company identifier	*427/Datastream*
GICS Industry	training	industry code	*427*
physical risk scores	training	various physical risk scores (see figure **??**)	*427*
Returns	both	total monthly return index (code: RI)	*Datastream/WRDS*
Size	both	measured by market equity (code: MV)	*Datastream/WRDS*
Land	training	real estate held for productive use (code: WC18375)	*Datastream*
CO_2	training	The estimated total CO2 and CO2 equivalents emission in tonnes (code: ENERDP123)	*Datastream*
Physical risk exposure	training	does the company acknowledge it has physical risks (code: CDP_PHYSICAL_RISK_EXP)	*CDP*
Physical risk explanation	training	(code: CDP_PHYSICAL_RISK_EXP_DES and CDP_EX_WHY_NOT_EXP_TO_PHYS_RISKS)	*CDP*
Emission reduction target	training	does the firm have an emission reduction target (code: CDP_TARGET)	*CDP*
Emissions intensity	training	CO_2 emission intensity relative to Paris Agreement	*TPI*
Risk factors	both	risk-free rate, market, size, value, momentum, portfolios	French (2018)
Risk factors	both	emerging market risk factors (market, size, value, momentum). Up to 2013.	Marmi (2013)
Risk factors	both	betting against beta, quality minus junk, up minus down	AQR (2018)

TPI = Transition Pathway Initiative — more information available here. 427 = Four Twenty-Seven, a leading climate risk and data company.
Sample = training or validation.

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[1] Environmental refers to physical and transition risk factors.

[2] I thank Christian Hansen for code. Available here.

[3] More information on *Four Twenty Seven* is available here.

Figure 3. Physical Risk Factor Descriptive Statistics

Factor	Description	Mean %	Variance	St. Dev %	Min	Max	2008-2017 Return %	Obs.
WET	extreme rainfall	-.22	19.11	4.37	-17.78	8.62	-25.83	848,497
HOT	heat stress	-.64	18.47	4.30	-9.08	16.96	-77.10	847,923
427_L	adjusted for land	-.02	11.81	3.44	-11.16	9.44	-2.80	848,246
427_I	adjusted for industry	.51	7.42	2.72	-5.17	9.27	61.12	799,813
427_U	total unadjusted score	.40	6.22	2.50	-5.38	7.37	48.26	780,645
CDP	*CDP* physical risk	-.14	7.20	2.68	-6.30	8.05	-16.32	821,346

Figure 4. Cumulative Returns of the Global Physical Risk Factors (%)

Figure 5. Correlation Matrix of the Global Physical Risk Factors and Traditional Factors

	MKT	SMB	HML	WML	BAB	QMJ	UMD	
WET	0.282**	0.204*	-0.0104	-0.151	0.0653	-0.286**	-0.168	
HOT	-0.103	-0.216*	-0.0657	0.0718	-0.225*	0.158	0.0960	
CDP	0.0778	-0.0455	0.0948	-0.119	-0.154	-0.117	-0.119	
427_L	0.137	0.0792	0.0255	-0.141	0.00562	-0.213*	-0.165	
427_I	0.237**	0.0245	0.198*	-0.172	-0.143	-0.210*	-0.190*	
427_U	0.284**	0.132	0.203*	-0.222*	-0.0241	-0.277**	-0.248**	
CO_{2P}	0.117	0.0423	-0.0795	-0.0624	0.237**	-0.0600	-0.0985	
CO_{2T}	0.214*	0.164	0.0278	-0.156	0.133	-0.213*	-0.189*	
	WET	HOT	CDP	427_L	427_I	427_U	CO_{2P}	CO_{2T}
WET	1.00							
HOT	0.00523	1.00						
CDP	0.159	0.0165	1.00					
427_L	0.534***	0.312***	0.209*	1.00				
427_I	0.327***	0.0645	-0.0661	0.309***	1.00			
427_U	0.299***	0.0997	-0.0168	0.369***	0.778***	1.00		
CO_{2P}	-0.0475	-0.108	-0.0593	-0.142	-0.141	-0.00183	1.00	
CO_{2T}	0.0723	-0.196*	-0.185*	-0.0781	-0.0442	0.108	0.237**	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 6. 427_L factor: Global decile portfolio performance

	Low Risk	2	3	4	5	6	7	8	9	High Risk
Intercept	-2.147**	-2.132***	-1.821**	-2.269**	-0.803	-1.827*	-1.192	-2.492**	-1.666*	-1.440*
	(-3.28)	(-3.58)	(-2.64)	(-3.00)	(-0.94)	(-2.53)	(-1.42)	(-3.21)	(-2.45)	(-2.06)
MKT	0.276	0.300*	0.302	0.312	-0.0258	0.292	0.613**	0.250	0.466**	0.421**
	(1.87)	(2.24)	(1.94)	(1.83)	(-0.13)	(1.79)	(3.23)	(1.43)	(3.04)	(2.67)
SMB	0.956*	0.260	1.142*	0.743	-0.0515	0.794	1.687**	1.277*	0.833	0.680
	(2.01)	(0.60)	(2.28)	(1.35)	(-0.08)	(1.51)	(2.76)	(2.26)	(1.69)	(1.34)
HML	-0.292	-0.131	-0.829*	-0.568	-0.746	-0.409	-0.564	-0.747	-0.485	-0.494
	(-0.73)	(-0.36)	(-1.99)	(-1.24)	(-1.45)	(-0.94)	(-1.11)	(-1.58)	(-1.18)	(-1.16)
WML	-0.311	0.115	-0.228	-0.334	-0.0576	-0.281	-0.411	-0.295	-0.0779	0.0501
	(-1.54)	(0.63)	(-1.08)	(-1.43)	(-0.22)	(-1.26)	(-1.59)	(-1.23)	(-0.37)	(0.23)
427_L	-0.394*	0.0399	-0.661**	-0.139	-0.00158	-0.135	0.259	0.796***	0.766***	0.400
	(-2.06)	(0.23)	(-3.28)	(-0.63)	(-0.01)	(-0.64)	(1.05)	(3.51)	(3.86)	(1.96)
Adj. R^2 $5F$	0.084*	0.006	0.125***	0.044	-0.023	0.041	0.185	0.166***	0.205***	0.086*
Adj. R^2 $4F$	0.0584	0.0145	0.0508	0.0494	-0.0138	0.0455	0.1841	0.0845	0.1092	0.0632

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 7. *WET* factor: Global decile portfolio performance

	Low Risk	2	3	4	5	6	7	8	9	High Risk
Intercept	-1.882**	-1.607*	-0.979	-0.694	-1.207	-1.354	-2.529***	-1.523*	-1.736*	-1.153
	(-2.84)	(-2.19)	(-1.13)	(-0.74)	(-1.57)	(-1.54)	(-3.39)	(-2.36)	(-2.36)	(-1.20)
MKT	0.271	0.272	0.361	0.474*	0.383*	0.464*	0.545**	0.316*	0.194	0.185
	(1.77)	(1.60)	(1.81)	(2.17)	(2.15)	(2.28)	(3.16)	(2.12)	(1.14)	(0.83)
SMB	0.887	0.468	1.536*	0.392	1.244*	1.115	1.023	0.412	0.724	-0.387
	(1.82)	(0.87)	(2.42)	(0.57)	(2.20)	(1.72)	(1.87)	(0.87)	(1.34)	(-0.55)
HML	-0.362	0.123	-0.920	-0.618	-0.861	-0.570	-0.315	-0.174	-0.595	-0.180
	(-0.90)	(0.28)	(-1.75)	(-1.08)	(-1.84)	(-1.07)	(-0.70)	(-0.45)	(-1.33)	(-0.31)
WML	-0.00729	0.279	-0.533*	-0.178	-0.719**	-0.0336	-0.201	-0.00794	-0.130	-0.0338
	(-0.04)	(1.25)	(-2.02)	(-0.62)	(-3.06)	(-0.12)	(-0.88)	(-0.04)	(-0.58)	(-0.12)
WET	-0.639***	0.100	-0.344	0.217	0.129	0.0813	0.247	0.348*	0.868***	0.537*
	(-4.01)	(0.57)	(-1.66)	(0.96)	(0.70)	(0.38)	(1.38)	(2.25)	(4.91)	(2.32)
Adj. R^2 5F	0.099***	0.000	0.094	0.047	0.183	0.053	0.157	0.088*	0.232***	0.026*
Adj. R^2 4F	-0.0188	0.0061	0.0803	0.0480	0.1867	0.0597	0.1502	0.0563	0.0777	-0.0110

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 8. *HOT* factor: Global decile portfolio performance

	Low Risk	2	3	4	5	6	7	8	9	High Risk
Intercept	-2.321**	-2.121**	-2.568***	-1.211	-1.529*	-1.759*	-1.902*	-2.261**	-2.741***	-1.635*
	(-2.93)	(-3.10)	(-4.18)	(-1.76)	(-2.26)	(-2.15)	(-2.35)	(-2.75)	(-3.70)	(-2.24)
MKT	0.474**	0.380*	0.351*	0.407**	0.625***	0.436*	0.210	0.369*	0.435**	0.222
	(2.68)	(2.49)	(2.56)	(2.64)	(4.13)	(2.39)	(1.16)	(2.00)	(2.63)	(1.36)
SMB	1.014	0.488	1.122*	0.851	0.442	0.144	1.323*	1.173	0.424	-0.419
	(1.74)	(0.97)	(2.49)	(1.68)	(0.89)	(0.24)	(2.22)	(1.94)	(0.78)	(-0.78)
HML	-0.470	-0.498	-0.363	-0.328	-0.930*	-0.957	-0.922	-1.070*	-0.382	-0.362
	(-0.99)	(-1.21)	(-0.98)	(-0.79)	(-2.29)	(-1.95)	(-1.89)	(-2.16)	(-0.86)	(-0.82)
WML	-0.382	-0.113	-0.162	0.170	0.337	-0.306	-0.370	-0.504*	-0.188	-0.0112
	(-1.59)	(-0.55)	(-0.87)	(0.81)	(1.64)	(-1.23)	(-1.50)	(-2.02)	(-0.84)	(-0.05)
HOT	-0.996***	-0.932***	-0.523***	-0.439**	-0.388*	-0.260	-0.277	0.890***	-0.291	-0.0660
	(-5.36)	(-5.81)	(-3.63)	(-2.72)	(-2.45)	(-1.36)	(-1.46)	(4.61)	(-1.67)	(-0.39)
Adj. R^2 5F	0.307***	0.280***	0.218***	0.122**	0.183**	0.074	0.090	0.199***	0.085	-0.016
Adj. R^2 4F	0.1396	0.0750	0.1350	0.0735	0.1471	0.0673	0.0807	0.0577	0.0709	-0.0086

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 9. Comparison with the Fama and French (1993) 4-factor model

Model	Average adj. R^2
4F	.0995
4F + 427_L	.101
4F + HOT	.0994
4F + WET	.0979

4F is the Fama and French (1993) 3-factor model with momentum. The model is run on 19,665 individual firms between January 2008 - December 2017 with monthly returns from Compustat. Data trimming is explained in the Empirical Strategy.

Figure 10. Fama and French (1993) 4-factor model assessment

Factor	Average β	# 5% level	# 1% level
MKT	.7228206	8,419 (43%)	6,692 (34%)
SMB	1.335469	3,750 (19%)	2,254 (11%)
HML	-.4795054	3,317 (17%)	2,095 (11%)
WML	-.2773698	3,249 (17%)	2,248 (11%)

4F is the Fama and French (1993) 3-factor model with momentum. The model is run on 19,665 individual firms between January 2008 - December 2017 with monthly returns from Compustat. Data trimming is explained in the Empirical Strategy. % of firms (rounded).

Figure 11. 427_L 5-factor model assessment

Factor	Average β	# 5% level	# 1% level
MKT	.8248488	8,505 (43%)	6,752 (34%)
SMB	1.11768	3,846 (20%)	2,351 (12%)
HML	-.2465932	3,445 (18%)	2,239 (11%)
WML	-.6397632	3,340 (17%)	2,317 (12%)
427_L	-.0293909	2,663 (14%)	2,663 (14%)

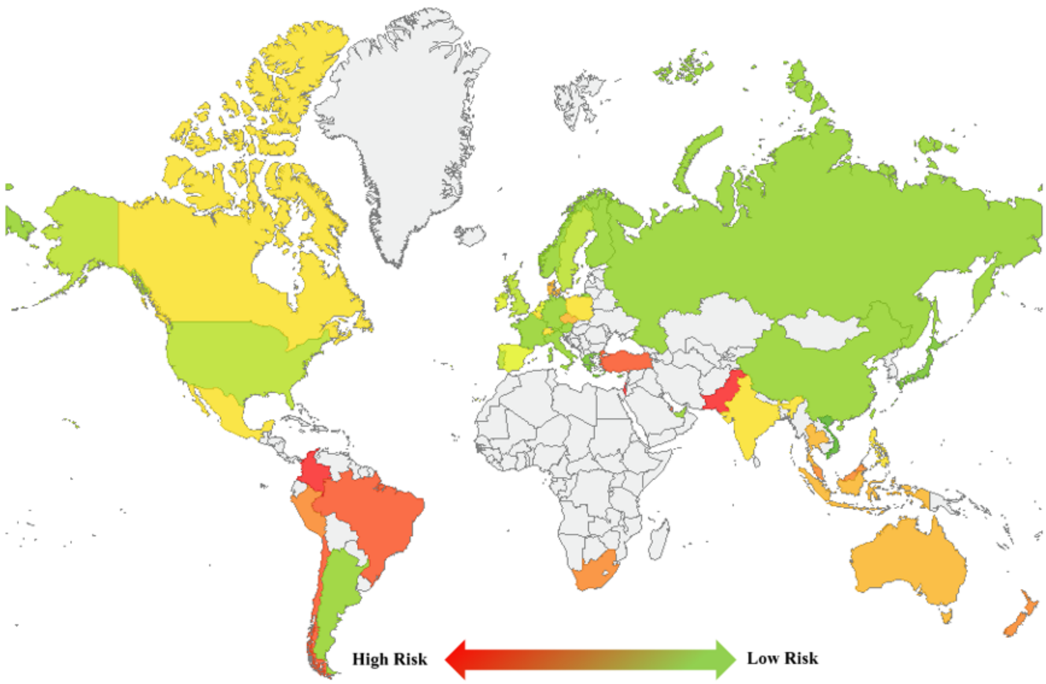
4F is the Fama and French (1993) 3-factor model
with momentum. The model is run on 19,665
individual firms between January 2008 -
December 2017 with monthly returns from Compustat.
Data trimming is explained in the Empirical Strategy. % are rounded.

Figure 12. Results from the Feng et al. (2019) and Belloni et al. (2014) method

Sort	MKT	SMB	HML	WML	BAB	QMJ	UMD	427_L	WET	HOT	427_U	427_I	CDP	$CO2_T$	$CO2_P$
Size & Investment (6)	6	3	3	1		2									
Size & Momentum (6)	6	3	1			1									
Size & Profitability (6)	6	4	1			2									
Size & Value (6)	6	4	4			2									
Size & WET (10)	1		1		1			2	1	2					4
Size & HOT (10)						1		1	2	3	1				5
Size & 427_L (10)						1			1	1	1				6
Size & $CO2_P$ (20)	1	1			3	4				2	1			2	6
Size & $CO2_T$ (20)	1				3	2				1	2			3	17

Number in brackets denote the number of deciles for each sort. The table shows the number of factors that pass the test across all relevant deciles.

HOT β



427 Heat Stress

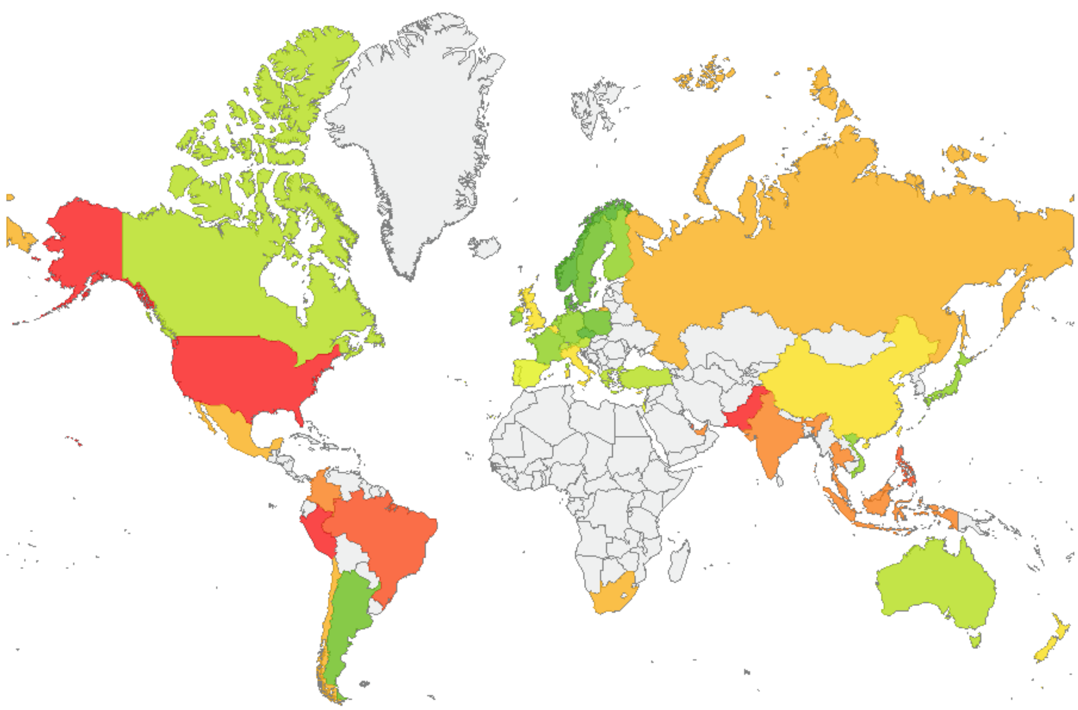
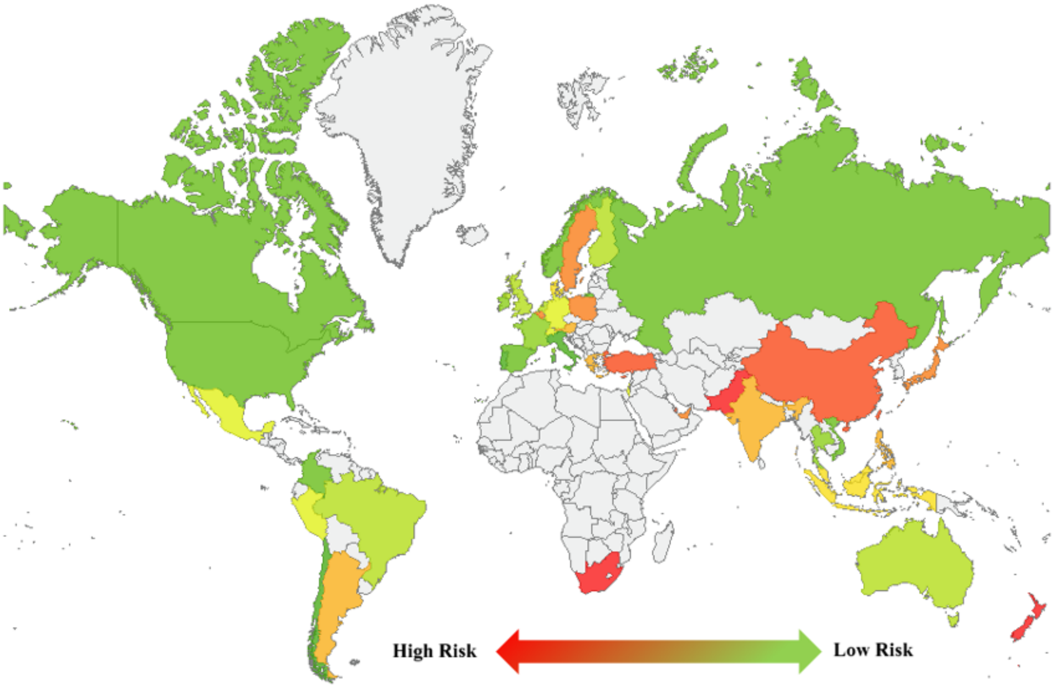


Figure 13. Heat stress comparison

$WET\ \beta$



427 Extreme Rainfall

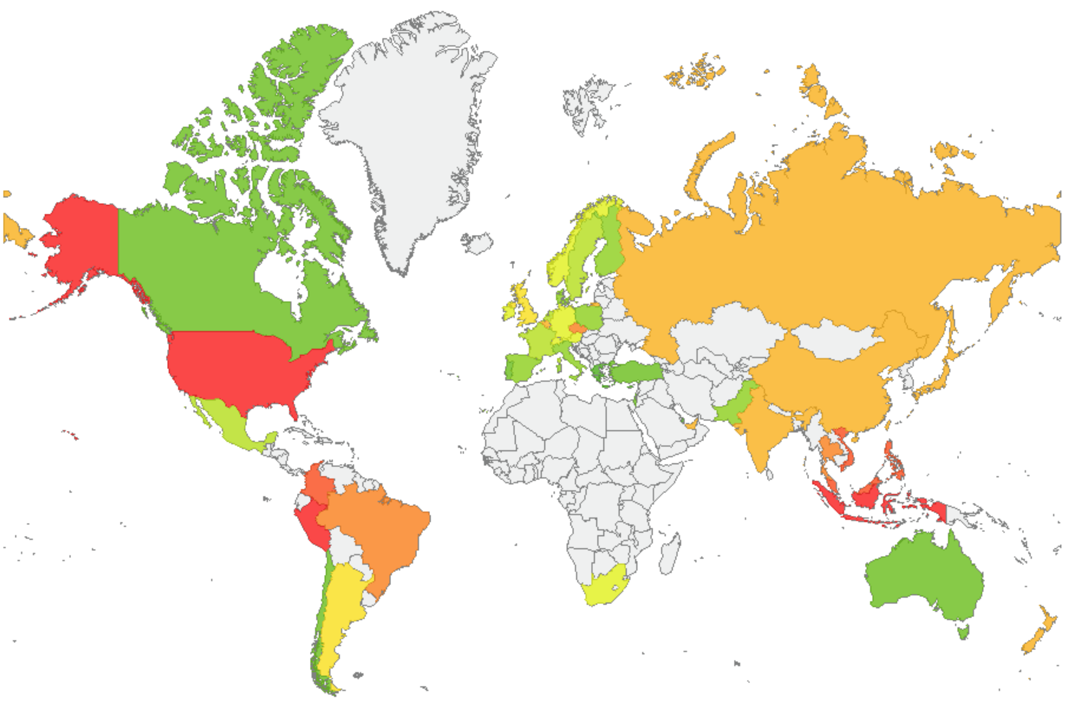
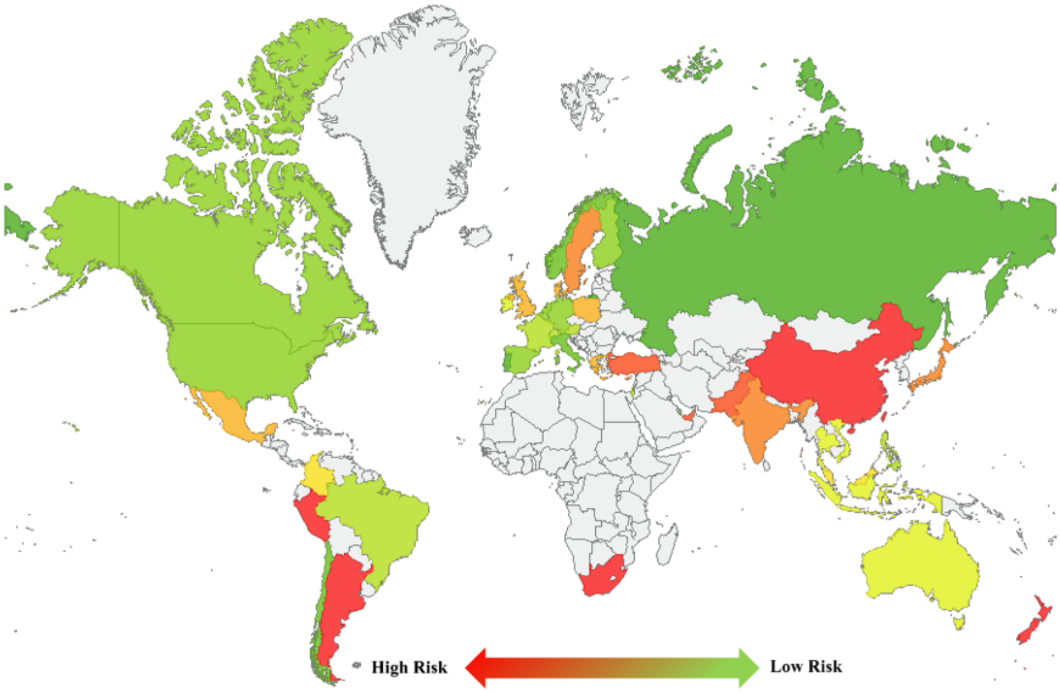


Figure 14. Extreme rainfall comparison

$427_L\ \beta$



427 Overall Risk

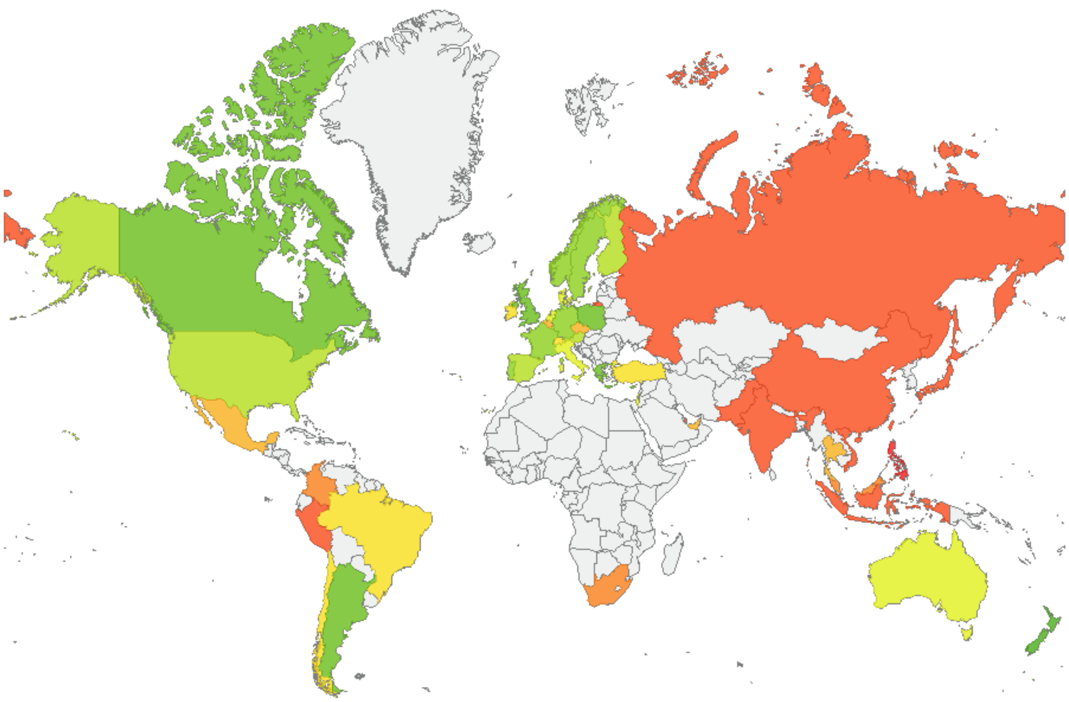


Figure 15. 427 overall risk comparison

Appendix B. INTERNET APPENDIX

Figure 16. 427_L factor: North American decile portfolio performance

	Low Risk	2	3	4	5	6	7	8 -
Intercept	0.345	-1.770*	-1.339	-1.365	-1.527*	-2.005**	-1.869**	-1.577*
	(0.63)	(-2.53)	(-1.66)	(-1.62)	(-2.07)	(-2.95)	(-3.22)	(-2.19)
MKT	-0.0470	0.331	0.363	0.474*	0.243	0.399*	0.264	0.417*
	(-0.34)	(1.90)	(1.81)	(2.26)	(1.32)	(2.35)	(1.82)	(2.33)
SMB	-0.0664	0.0855	-0.305	0.0424	-0.0106	-0.314	-0.492	-0.0402
	(-0.24)	(0.24)	(-0.74)	(0.10)	(-0.03)	(-0.91)	(-1.66)	(-0.11)
HML	-0.0253	-0.434	-0.0542	-0.288	-0.0644	0.0708	-0.248	-0.405
	(-0.10)	(-1.35)	(-0.15)	(-0.74)	(-0.19)	(0.23)	(-0.93)	(-1.22)
WML	-0.198	-0.325	-0.0750	-0.164	0.0852	-0.0389	0.189	-0.146
	(-1.33)	(-1.71)	(-0.34)	(-0.72)	(0.43)	(-0.21)	(1.20)	(-0.75)
427_L	0.0106	-0.373**	-0.365*	-0.355*	0.0333	-0.0718	0.163	0.341**
	(0.11)	(-3.07)	(-2.61)	(-2.43)	(0.26)	(-0.61)	(1.62)	(2.73)
Adj. R^2 $5F$	-0.026	0.114**	0.058**	0.080*	-0.025	0.020	0.042*	0.077**
Adj. R^2 $4F$	-0.0169	0.0817	0.0109	0.0410	-0.0170	0.0253	0.0282	0.0253

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *427* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (MKT), size (SMB), value (HML), and momentum (WML). 5F adds the 427_L factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample.

Figure 17. *HOT* factor: North American decile portfolio performance

	Low Risk	2	3	4	5	6	7	8	9	High Risk
Intercept	-0.350	0.688	-1.106	-0.444	-1.082	-1.995**	-0.865	-0.0651	-1.548	-2.113**
	(-0.64)	(1.28)	(-1.24)	(-1.15)	(-1.63)	(-2.93)	(-0.95)	(-0.15)	(-1.98)	(-2.90)
MKT	-0.0589	-0.143	0.311	0.0731	0.256	0.493**	0.314	-0.0457	0.232	0.255
	(-0.43)	(-1.06)	(1.39)	(0.75)	(1.53)	(2.89)	(1.38)	(-0.41)	(1.18)	(1.40)
SMB	-0.0461	0.223	-0.128	-0.00499	-0.0886	-0.490	-0.142	0.186	-0.705	0.00689
	(-0.17)	(0.82)	(-0.28)	(-0.03)	(-0.26)	(-1.42)	(-0.31)	(0.83)	(-1.78)	(0.02)
HML	0.0605	-0.247	-0.263	0.0961	-0.0389	-0.370	-0.358	0.00691	-0.0484	-0.240
	(0.24)	(-1.01)	(-0.65)	(0.54)	(-0.13)	(-1.19)	(-0.86)	(0.03)	(-0.14)	(-0.72)
WML	0.0291	-0.320*	-0.397	0.0362	0.122	-0.264	-0.350	-0.141	0.116	-0.106
	(0.20)	(-2.21)	(-1.65)	(0.35)	(0.68)	(-1.44)	(-1.43)	(-1.18)	(0.55)	(-0.54)
HOT	-0.0686	-0.402**	-0.648**	0.114	-0.167	-0.160	0.0619	0.359***	0.306	0.122
	(-0.54)	(-3.24)	(-3.15)	(1.27)	(-1.09)	(-1.02)	(0.29)	(3.52)	(1.69)	(0.73)
Adj. R^2 $5F$	-0.038	0.080*	0.099*	-0.021	-0.002	0.079	0.001	0.093***	0.009	-0.013
Adj. R^2 $4F$	-0.0315	0.0033	0.0296	-0.0268	-0.0038	0.0785	0.0088	0.0030	-0.0074	-0.0093

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing. This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.

Figure 18. *WET* factor: North American decile portfolio performance

	Low Risk	2	3	4	5	6	7	8	9	High Risk
Intercept	-0.680	-1.104	0.220	-1.227	-0.514	-0.817	-0.913	-0.0762	-1.828*	-0.847
	(-1.21)	(-1.55)	(0.31)	(-1.85)	(-0.57)	(-1.35)	(-1.27)	(-0.21)	(-2.59)	(-1.50)
MKT	0.0815	0.204	0.0701	0.279	0.203	-0.0239	0.226	-0.0277	0.0130	0.0485
	(0.58)	(1.15)	(0.40)	(1.69)	(0.91)	(-0.16)	(1.26)	(-0.30)	(0.07)	(0.34)
SMB	-0.217	-0.0861	0.570	-0.0640	0.0151	0.178	0.122	-0.131	-0.0658	0.205
	(-0.77)	(-0.24)	(1.59)	(-0.19)	(0.03)	(0.58)	(0.34)	(-0.70)	(-0.19)	(0.72)
HML	0.140	0.0166	-0.475	-0.0231	0.264	-0.0902	-0.268	-0.0607	0.316	-0.229
	(0.55)	(0.05)	(-1.49)	(-0.08)	(0.66)	(-0.33)	(-0.83)	(-0.36)	(1.00)	(-0.90)
WML	-0.0240	-0.0680	-0.565**	-0.184	-0.289	0.210	-0.157	-0.0561	0.248	0.0592
	(-0.16)	(-0.36)	(-3.01)	(-1.05)	(-1.22)	(1.31)	(-0.82)	(-0.57)	(1.33)	(0.40)
WET	-0.446***	-0.497***	-0.720***	-0.421***	-0.521***	-0.396***	-0.391***	0.0323	0.323**	0.203*
	(-5.74)	(-5.09)	(-7.37)	(-4.60)	(-4.23)	(-4.75)	(-3.94)	(0.63)	(3.33)	(2.61)
Adj. R^2 $5F$	0.220***	0.189***	0.366***	0.186***	0.147***	0.159***	0.132***	-0.029	0.073***	0.030**
Adj. R^2 $4F$	0.0036	0.0136	0.0723	0.0430	0.0218	0.0017	0.0228	-0.0239	-0.0087	-0.0190

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.

This table shows portfolios formed on their *WET* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *WET* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.

Data comes from the training sample.

Figure 19. 427_L factor: European decile portfolio performance

	Low Risk	2	3	4	5	6	7	8-
Intercept	-0.609	-1.063	-1.869***	-0.0714	0.150	-0.00714	-1.279	-2.826***
	(-0.92)	(-1.64)	(-3.66)	(-0.21)	(0.26)	(-0.01)	(-1.95)	(-3.78)
MKT	0.196	0.282*	0.146	-0.0460	-0.0869	0.0979	0.245	0.379*
	(1.45)	(2.14)	(1.41)	(-0.66)	(-0.75)	(0.79)	(1.84)	(2.49)
SMB	1.072**	-0.365	0.339	0.148	0.170	0.539	0.698	0.631
	(2.96)	(-1.03)	(1.22)	(0.79)	(0.54)	(1.62)	(1.95)	(1.55)
HML	-0.516	-0.0383	-0.0375	0.160	0.0462	0.125	-0.370	-0.0711
	(-1.55)	(-0.12)	(-0.15)	(0.92)	(0.16)	(0.41)	(-1.13)	(-0.19)
WML	-0.608**	0.0537	0.0845	0.0631	-0.0218	0.354*	-0.117	0.131
	(-3.19)	(0.29)	(0.58)	(0.64)	(-0.13)	(2.02)	(-0.62)	(0.61)
427_L	-0.665***	-1.385***	-0.973***	-0.244**	-0.339**	-0.394**	-0.686***	-0.0595
	(-4.66)	(-9.97)	(-8.88)	(-3.29)	(-2.76)	(-3.01)	(-4.87)	(-0.37)
Adj. R^2 $5F$	0.352***	0.493***	0.448***	0.071***	0.039**	0.100**	0.256***	0.041
Adj. R^2 $4F$	0.2346	0.0582	0.0745	-0.0089	-0.0161	0.0366	0.1087	0.0485

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *427* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (MKT), size (SMB), value (HML), and momentum (WML). 5F adds the 427_L factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample.

Figure 20. *HOT* factor: European decile portfolio performance

	Low Risk	2	3	4	5	6	7	8	9-
Intercept	0.133	0.280	-0.375	-0.945	-1.112	-2.346***	-1.024	-0.456	-0.657*
	(0.22)	(0.42)	(-0.74)	(-1.86)	(-1.92)	(-3.50)	(-1.29)	(-0.83)	(-2.16)
MKT	0.124	-0.182	0.000264	0.131	0.0814	0.153	0.212	0.0903	0.00250
	(1.01)	(-1.35)	(0.00)	(1.28)	(0.70)	(1.14)	(1.33)	(0.81)	(0.04)
SMB	0.830*	0.255	0.663*	0.376	0.231	0.133	0.0819	0.937**	0.182
	(2.57)	(0.72)	(2.49)	(1.40)	(0.76)	(0.37)	(0.20)	(3.21)	(1.13)
HML	-0.550	0.366	0.345	-0.141	0.139	-0.0218	0.0630	0.168	0.0831
	(-1.84)	(1.12)	(1.40)	(-0.57)	(0.49)	(-0.07)	(0.16)	(0.62)	(0.56)
WML	-0.692***	0.112	0.138	0.106	0.0852	0.0147	-0.0944	0.104	0.00777
	(-4.08)	(0.61)	(0.99)	(0.75)	(0.53)	(0.08)	(-0.43)	(0.68)	(0.09)
HOT	-0.625***	-0.267**	-0.000557	-0.759***	-0.639***	-0.711***	-0.690***	0.138	0.0669
	(-6.80)	(-2.65)	(-0.01)	(-9.92)	(-7.33)	(-7.04)	(-5.79)	(1.66)	(1.46)
Adj. R^2 $5F$	0.458***	0.042*	0.029	0.509***	0.343***	0.331***	0.265***	0.056	-0.013
Adj. R^2 $4F$	0.2450	-0.0083	0.0370	0.0928	0.0419	0.0480	0.0574	0.0416	-0.0234

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*),
size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample.

Figure 21. *WET* factor: European decile portfolio performance

	Low Risk	2	3	4	5	6	7	8-
Intercept	-1.343*	-1.349*	0.149	-1.731*	-2.368***	-0.702	-1.710*	-0.324*
	(-2.11)	(-2.52)	(0.28)	(-2.51)	(-3.62)	(-1.45)	(-2.16)	(-2.25)
MKT	0.186	0.229*	0.00778	0.257	0.277*	-0.0240	0.425**	-0.00139
	(1.48)	(2.17)	(0.07)	(1.89)	(2.15)	(-0.25)	(2.72)	(-0.05)
SMB	1.061**	0.852**	0.443	0.940**	0.818*	0.342	1.552***	-0.0542
	(3.24)	(3.11)	(1.63)	(2.65)	(2.44)	(1.38)	(3.82)	(-0.73)
HML	0.0478	-0.534*	0.495	0.0345	-0.555	0.0388	-0.477	0.00320
	(0.15)	(-2.06)	(1.93)	(0.10)	(-1.76)	(0.17)	(-1.24)	(0.05)
WML	0.0405	-0.167	0.190	0.0974	-0.0646	0.0266	-0.0924	0.00594
	(0.23)	(-1.12)	(1.29)	(0.51)	(-0.36)	(0.20)	(-0.42)	(0.15)
WET	-0.591***	-0.700***	-0.201*	-0.321*	-0.387**	0.0242	0.0764	0.0427
	(-4.95)	(-6.99)	(-2.03)	(-2.48)	(-3.17)	(0.27)	(0.52)	(1.58)
Adj. R^2 $5F$	0.237***	0.373***	0.048*	0.107*	0.143**	-0.025	0.131	-0.014
Adj. R^2 $4F$	0.0811	0.11140	0.0221	0.0668	0.0760	-0.0162	0.1370	-0.0276

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *WET* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *WET* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample.

Figure 22. *427*$_L$ factor: Japanese decile portfolio performance

	-6	7	8	9	High Risk
Intercept	-1.122*	0.220	0.0274	-0.0642	-0.340
	(-2.11)	(0.37)	(0.05)	(-0.42)	(-0.69)
MKT	-0.0569	0.0408	0.222	-0.00636	0.00597
	(-0.47)	(0.30)	(1.76)	(-0.18)	(0.05)
SMB	0.0508	-0.0251	-0.152	0.0707	-0.0836
	(0.21)	(-0.09)	(-0.61)	(1.00)	(-0.37)
HML	0.211	0.0992	0.467*	-0.141*	0.0607
	(0.97)	(0.41)	(2.08)	(-2.23)	(0.30)
WML	0.114	-0.478**	0.152	-0.0638	0.292*
	(0.77)	(-2.91)	(1.00)	(-1.49)	(2.14)
427$_L$	1.207***	2.256***	2.077***	1.987***	1.642***
	(9.33)	(15.64)	(15.61)	(52.99)	(13.72)
Adj. R^2 $5F$	0.431***	0.721***	0.701***	0.966***	0.636***
Adj. R^2 $4F$	0.0045	0.1314	0.0701	0.1395	0.0443

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their *427* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *427*$_L$ factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.

Figure 23. *HOT* factor: Japanese decile portfolio performance

	Low Risk	2	3	4	5	6-
Intercept	0.214	-0.152	-0.180	0.0563	-0.193	-0.0738
	(0.72)	(-0.45)	(-0.56)	(0.10)	(-0.29)	(-0.20)
MKT	0.0523	-0.00756	-0.0282	-0.160	0.0661	-0.131
	(0.76)	(-0.10)	(-0.38)	(-1.19)	(0.43)	(-1.56)
SMB	-0.145	0.167	0.0978	0.107	-0.137	-0.0518
	(-1.07)	(1.09)	(0.67)	(0.40)	(-0.44)	(-0.31)
HML	0.228	-0.271	-0.0208	0.0454	0.0617	-0.0107
	(1.88)	(-1.98)	(-0.16)	(0.19)	(0.22)	(-0.07)
WML	-0.0663	0.0924	0.0446	0.167	0.230	0.0260
	(-0.80)	(0.98)	(0.49)	(1.02)	(1.21)	(0.25)
HOT	-2.321***	-1.943***	-1.722***	-0.716***	-1.216***	-0.229**
	(-33.30)	(-24.66)	(-22.86)	(-5.23)	(-7.68)	(-2.67)
Adj. R^2 $5F$	0.918***	0.863***	0.838***	0.177***	0.347***	0.029**
Adj. R^2 $4F$	0.1238	0.1397	0.1046	-0.0115	0.0178	-0.0228

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993) . 4F is the 4-factor model: market (*MKT*),
size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample.

Figure 24. *WET* factor: Japanese decile portfolio performance

	-4	5	6	7	8	9-
Intercept	-0.283	-0.533	0.0514	-0.898	-0.0822	0.103
	(-0.92)	(-0.87)	(0.08)	(-1.49)	(-0.27)	(0.18)
MKT	-0.0483	0.262	0.235	0.106	-0.0508	0.0251
	(-0.68)	(1.86)	(1.59)	(0.77)	(-0.72)	(0.19)
SMB	-0.125	0.342	-0.374	0.180	0.0940	-0.372
	(-0.88)	(1.21)	(-1.27)	(0.65)	(0.67)	(-1.41)
HML	0.0146	-0.387	-0.0839	-0.466	-0.131	-0.000227
	(0.12)	(-1.55)	(-0.32)	(-1.90)	(-1.06)	(-0.00)
WML	0.0394	-0.692***	0.113	-0.328	-0.154	0.177
	(0.46)	(-4.08)	(0.64)	(-1.97)	(-1.83)	(1.12)
WET	0.151	1.631***	1.857***	1.841***	1.975***	1.778***
	(1.88)	(10.23)	(11.12)	(11.76)	(24.88)	(11.94)
Adj. R^2 $5F$	-0.009	0.581***	0.544***	0.600***	0.856***	0.558***
Adj. R^2 $4F$	-0.0313	0.2037	0.0574	0.1229	0.0851	0.0139

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

'-': neighbour decile missing. This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993)
. 4F is the 4-factor model: market (*MKT*),
size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds
the *HOT* factor. An F-test is run between the 4F and 5F models
with p-level signif. given on the 5F row. Data comes from the training sample.

Figure 25. 427_L factor: Asia Pacific decile portfolio performance

	Low Risk	2	3	4...	...7	8	9	High Risk
Intercept	-0.318	-2.121***	-0.708	-0.505*	-0.160	-1.162**	-1.036**	-2.483**
	(-1.02)	(-4.09)	(-0.89)	(-2.00)	(-0.16)	(-3.01)	(-2.77)	(-3.18)
MKT	-0.0284	0.00346	0.215	-0.0402	0.0775	-0.0468	0.0799	0.142
	(-0.56)	(0.04)	(1.67)	(-0.98)	(0.49)	(-0.75)	(1.32)	(1.12)
SMB	-0.0187	0.336	0.631*	0.0233	1.051**	0.138	-0.0890	0.657*
	(-0.16)	(1.77)	(2.17)	(0.25)	(2.93)	(0.97)	(-0.65)	(2.29)
HML	-0.0197	0.298	0.125	-0.0492	-0.0494	0.0862	0.200	0.0880
	(-0.16)	(1.42)	(0.39)	(-0.48)	(-0.13)	(0.55)	(1.33)	(0.28)
WML	-0.00722	0.191	0.190	0.0393	0.125	-0.0172	-0.0428	0.239
	(-0.09)	(1.48)	(0.97)	(0.63)	(0.51)	(-0.18)	(-0.46)	(1.23)
427_L	-0.139*	-0.648***	-0.939***	-0.0686	0.577**	0.113	0.115	0.00618
	(-2.51)	(-7.05)	(-6.67)	(-1.54)	(3.33)	(1.66)	(1.73)	(0.04)
Adj. R^2 $5F$	0.012*	0.315***	0.341***	-0.013	0.107***	0.002	0.011	0.026
Adj. R^2 $4F$	-0.0338	0.0246	0.0908	-0.0246	0.0290	-0.0133	-0.0065	0.0343

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *427* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the 427_L factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample. '...': skipped for brevity & no significant result.

Figure 26. *HOT* factor: Asia Pacific decile portfolio performance

	Low Risk	2	3...	...5	6	7	8	9	High Risk
Intercept	-0.498	-1.554***	0.175	0.146	-0.681*	-1.603	-0.578*	-0.768	-1.097**
	(-0.96)	(-3.63)	(0.36)	(0.41)	(-2.25)	(-1.24)	(-2.02)	(-1.42)	(-3.12)
MKT	0.239**	-0.0297	0.0611	0.0194	-0.00224	0.0781	0.0203	0.0955	0.0692
	(2.96)	(-0.45)	(0.89)	(0.35)	(-0.05)	(0.39)	(0.46)	(1.14)	(1.27)
SMB	0.0787	0.163	0.193	-0.0198	0.00613	1.411**	0.138	0.464*	-0.162
	(0.41)	(1.03)	(1.07)	(-0.15)	(0.06)	(2.96)	(1.31)	(2.34)	(-1.26)
HML	0.116	0.255	0.184	-0.0362	0.0283	0.00620	0.236*	0.267	0.115
	(0.56)	(1.51)	(0.95)	(-0.26)	(0.24)	(0.01)	(2.09)	(1.25)	(0.83)
WML	-0.0592	0.0163	0.165	-0.00716	-0.0163	0.484	0.0882	0.00945	-0.0435
	(-0.47)	(0.16)	(1.38)	(-0.08)	(-0.22)	(1.53)	(1.26)	(0.07)	(-0.51)
HOT	-0.951***	-0.630***	-0.218**	0.0454	0.0104	-0.202	0.0903*	0.279***	0.0459
	(-13.68)	(-10.98)	(-3.32)	(0.95)	(0.26)	(-1.16)	(2.36)	(3.86)	(0.97)
Adj. R^2 5F	0.656***	0.525***	0.117***	-0.033	-0.042	0.079	0.050*	0.110***	0.005
Adj. R^2 4F	0.0981	0.0300	0.0400	-0.0325	-0.0335	0.0761	0.0124	0.0024	0.0049

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample. '...': skipped for brevity & no significant result.

Figure 27. *WET* factor: Asia Pacific decile portfolio performance

	Low Risk	2	3	4...	...6	7	8	9	High Risk
Intercept	-1.913**	-1.403	-0.405	-0.269	-0.727	-0.0624	-0.700*	-0.507	-2.284**
	(-2.71)	(-1.55)	(-1.27)	(-1.22)	(-1.61)	(-0.21)	(-2.45)	(-1.61)	(-3.00)
MKT	0.164	-0.0424	0.0146	-0.0272	-0.0426	-0.00756	-0.0394	-0.0193	0.128
	(1.44)	(-0.29)	(0.28)	(-0.76)	(-0.58)	(-0.16)	(-0.86)	(-0.38)	(1.04)
SMB	0.445	0.739*	-0.113	-0.00877	0.134	-0.0702	0.0244	0.0272	0.593*
	(1.65)	(2.13)	(-0.93)	(-0.10)	(0.78)	(-0.62)	(0.22)	(0.23)	(2.03)
HML	-0.0856	0.323	-0.160	-0.0989	0.222	-0.00977	-0.00612	-0.0208	0.113
	(-0.30)	(0.87)	(-1.22)	(-1.09)	(1.20)	(-0.08)	(-0.05)	(-0.16)	(0.36)
WML	0.0668	0.257	-0.0464	-0.0387	-0.0671	-0.00339	-0.0456	-0.0153	0.230
	(0.37)	(1.12)	(-0.58)	(-0.69)	(-0.59)	(-0.04)	(-0.63)	(-0.19)	(1.19)
WET	-0.715***	-1.098***	-0.0344	0.00681	-0.124	-0.0246	0.0175	0.00638	-0.117
	(-6.93)	(-8.26)	(-0.74)	(0.21)	(-1.88)	(-0.56)	(0.42)	(0.14)	(-1.05)
Adj. R^2 $5F$	0.353***	0.419***	-0.018	-0.027	0.015	-0.038	-0.032	-0.042	0.039
Adj. R^2 $4F$	0.0884	0.0799	-0.0140	-0.0184	-0.0062	-0.0323	-0.0250	-0.0329	0.0382

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. '-': neighbour decile missing.
This table shows portfolios formed on their *WET* physical risk score in a similar method to Fama and French (1993). 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *WET* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row.
Data comes from the training sample. '...': skipped for brevity & no significant result.

Figure 28. 427_L factor: Chinese decile portfolio performance

	-3-	-5-	7	8	9-
Intercept	0.296	-1.432	0.342	0.639	-0.277
	(1.00)	(-0.83)	(0.91)	(1.14)	(-0.35)
MKT	0.0129	0.0832	0.00160	-0.0796	0.168*
	(0.41)	(0.46)	(0.04)	(-1.36)	(2.03)
SMB	0.0365	0.114	0.0304	0.157	-0.0503
	(0.48)	(0.26)	(0.32)	(1.10)	(-0.25)
HML	0.0733	-0.438	0.0683	0.147	-0.0744
	(0.76)	(-0.78)	(0.56)	(0.81)	(-0.29)
WML	0.0219	0.112	-0.00305	0.0720	0.0166
	(0.24)	(0.21)	(-0.03)	(0.42)	(0.07)
427_L	0.0403	0.869***	0.0775	0.241***	1.506***
	(1.12)	(4.16)	(1.71)	(3.55)	(15.71)
Adj. R^2 $5F$	-0.049	0.234***	-0.029	0.123***	0.832***
Adj. R^2 $4F$	-0.0536	0.0189	-0.0630	-0.0521	0.1189

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their *427* physical risk score in a similar method to Fama and French (1993) &. 4F is the 4-factor model: market (MKT), size (SMB), value (HML), and momentum (WML). 5F adds the 427_L factor.
An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.
Sample is limited to January 2008 to March 2013.

Figure 29. *HOT* factor: Chinese decile portfolio performance

	-2	3	4	5	6-	-8	9-
Intercept	0.138	-0.104	-0.187	-1.228	0.375	-0.00165	0.842
	(0.95)	(-0.13)	(-1.21)	(-0.61)	(0.60)	(-0.00)	(0.96)
MKT	0.00637	0.0893	0.00692	0.183	-0.0305	0.0789	0.0486
	(0.42)	(1.04)	(0.43)	(0.88)	(-0.47)	(1.20)	(0.53)
SMB	0.00856	-0.138	-0.0357	-0.000540	0.0888	-0.0584	-0.0642
	(0.23)	(-0.67)	(-0.92)	(-0.00)	(0.56)	(-0.37)	(-0.29)
HML	-0.00205	-0.322	-0.0212	-0.744	0.0119	-0.304	-0.135
	(-0.05)	(-1.24)	(-0.44)	(-1.18)	(0.06)	(-1.53)	(-0.49)
WML	0.0189	-0.00399	-0.0378	0.190	0.101	-0.00192	0.0995
	(0.43)	(-0.02)	(-0.81)	(0.31)	(0.53)	(-0.01)	(0.37)
HOT	0.00629	-1.783***	0.0253	-0.559*	-0.0398	0.168	0.0964
	(0.32)	(-16.09)	(1.22)	(-2.07)	(-0.47)	(1.97)	(0.81)
Adj. R^2 $5F$	-0.079	0.834***	-0.034	0.070*	-0.066	0.016*	-0.069
Adj. R^2 $4F$	-0.0627	0.0974	-0.0429	0.0172	-0.0521	-0.0333	-0.0629

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993) &. 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor.
An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.
Sample is limited to January 2008 to March 2013.

Figure 30. *WET* factor: Chinese decile portfolio performance

	Low Risk-	-4	5-	8	9-
Intercept	-2.356	-0.124	-0.139	-2.769	0.320
	(-1.35)	(-0.29)	(-0.92)	(-1.68)	(0.51)
MKT	0.413^{*}	-0.0376	0.00117	0.426^{*}	0.0403
	(2.29)	(-0.84)	(0.07)	(2.51)	(0.62)
SMB	-0.380	0.0316	-0.0292	-0.227	-0.0145
	(-0.84)	(0.28)	(-0.74)	(-0.53)	(-0.09)
HML	-1.065	-0.0346	-0.0113	-1.021	-0.237
	(-1.90)	(-0.25)	(-0.23)	(-1.94)	(-1.17)
WML	0.265	0.0361	-0.0416	0.270	-0.0270
	(0.49)	(0.27)	(-0.88)	(0.53)	(-0.14)
WET	-0.840^{***}	0.00401	-0.00103	0.928^{***}	-0.00395
	(-3.90)	(0.07)	(-0.06)	(4.58)	(-0.05)
Adj. R^2 $5F$	0.211^{***}	-0.064	-0.061	0.338^{***}	-0.051
Adj. R^2 $4F$	0.0177	-0.0461	-0.0429	0.1103	-0.0333

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their *WET* physical risk score in a similar method to Fama and French (1993) &. 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *WET* factor. An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.
Sample is limited to January 2008 to March 2013.

Figure 31. 427_L factor: Brazilian decile portfolio performance

	Low Risk-	-4	5	6	7-
Intercept	0.259	0.580	0.341	0.0587	0.259
	(1.92)	(1.17)	(0.67)	(0.10)	(1.92)
MKT	0.0488	0.128	-0.0161	-0.0485	0.0488
	(1.70)	(1.21)	(-0.15)	(-0.37)	(1.70)
SMB	0.0721*	0.259	0.132	0.116	0.0721*
	(2.03)	(1.98)	(0.98)	(0.72)	(2.03)
HML	0.0512	0.119	-0.0847	-0.0389	0.0512
	(1.39)	(0.87)	(-0.61)	(-0.23)	(1.39)
WML	0.0563*	0.133	0.0751	-0.189	0.0563*
	(2.65)	(1.70)	(0.93)	(-1.97)	(2.65)
427_L	-0.182*	0.589*	0.487	-0.107	1.818***
	(-2.46)	(2.15)	(1.73)	(-0.32)	(24.53)
Adj. R^2 $5F$	0.107*	0.093*	0.027	0.034	0.912***
Adj. R^2 $4F$	0.0299	0.0365	-0.0068	0.0485	0.0060

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their *427* physical risk score in a similar method to Fama and French (1993) & . 4F is the 4-factor model: market (MKT), size (SMB), value (HML), and momentum (WML). 5F adds the 427_L factor.
An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.
Sample is limited to January 2008 to March 2013.

Figure 32. *HOT* factor: Brazilian decile portfolio performance

	-9	High Risk
Intercept	-0.378	0.384
	(-1.14)	(1.17)
MKT	-0.0300	0.0349
	(-0.43)	(0.50)
SMB	-0.0458	0.0535
	(-0.51)	(0.60)
HML	0.00624	-0.00489
	(0.07)	(-0.05)
WML	-0.0914	0.100
	(-1.77)	(1.95)
HOT	1.532***	0.474***
	(16.15)	(5.03)
Adj. R^2 $5F$	0.824***	0.312***
Adj. R^2 $4F$	0.0353	0.0235

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their *HOT* physical risk score in a similar method to Fama and French (1993) &. 4F is the 4-factor model: market (*MKT*), size (*SMB*), value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor.
An F-test is run between the 4F and 5F models with p-level signif. given on the 5F row. Data comes from the training sample.
Sample is limited to January 2008 to March 2013.

Figure 33. *WET* factor: Brazilian decile portfolio performance

	-8	9	High Risk
Intercept	-0.263	0.205	0.455
	(-0.44)	(0.53)	(1.18)
MKT	-0.131	0.0871	0.0678
	(-1.04)	(1.06)	(0.83)
SMB	-0.0276	0.0657	0.0479
	(-0.17)	(0.63)	(0.46)
HML	-0.174	0.102	0.0367
	(-1.08)	(0.97)	(0.35)
WML	-0.120	0.122*	0.104
	(-1.30)	(2.04)	(1.74)
WET	1.145***	0.717***	0.550***
	(6.75)	(6.49)	(5.00)
Adj. R^2 $5F$	0.445***	0.430***	0.297***
Adj. R^2 $4F$	0.0193	0.0193	0.0060

t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
'-': neighbour decile missing. This table shows portfolios formed on their
HOT physical risk score in a similar method to Fama and French (1993)
& . 4F is the 4-factor model: market (*MKT*), size (*SMB*),
value (*HML*), and momentum (*WML*). 5F adds the *HOT* factor.
An F-test is run between the 4F and 5F models with p-level signif. given on
the 5F row. Data comes from the training sample.
Sample is limited to January 2008 to March 2013.

Figure 34. *HOT* 5-factor model assessment

Factor	Average β	# 5% level	# 1% level
MKT	.6508546	8,471 (43%)	6,717 (34%)
SMB	.9812848	3,710 (19%)	2,321 (12%)
HML	-.1013022	3,444 (18%)	2,228 (11%)
WML	-.2324742	3,373 (17%)	1,992 (10%)
HOT	-.141694	2,778 (14%)	2,778 (14%)

4F is the Fama and French (1993) 3-factor model
with momentum. The model is run on 19,665
individual firms between January 2008 -
December 2017 with monthly returns from Compustat.
Data trimming is explained in the Empirical Strategy. % are rounded.

Figure 35. *WET* 5-factor model assessment

Factor	Average β	# 5% level	# 1% level
MKT	.6095514	8,372 (43%)	6,597 (34%)
SMB	2.583224	3,807 (19%)	2,360 (12%)
HML	-6.931488	3,442 (18%)	2,243 (11%)
WML	-.7072227	3,337 (17%)	2,371 (12%)
WET	-2.242901	2,720 (14%)	2,720 (14%)

4F is the Fama and French (1993) 3-factor model with momentum. The model is run on 19,665 individual firms between January 2008 - December 2017 with monthly returns from Compustat. Data trimming is explained in the Empirical Strategy. % are rounded.