Extreme precipitation risk and the cross-section of stock returns

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Abstract

Climate scientists have found an increasing trend toward heavy precipitation events since the 1950s. We investigate whether the extreme precipitation risk is priced in the cross-section of US stock returns. Using the recently developed Actuaries Climate Index, we construct a trading portfolio of extreme precipitation risk using the portfolio sort approach. From 1983 to 2022, the average return on stocks with higher sensitivity to extreme precipitation exceeds that for stocks with low sensitivities by 0.2 per cent annually, controlling for exposure to the market, size, value and momentum factors. Our results show that extreme precipitation risk is priced in the stock market, and the premium is small but positive.

JEL classification: G12, Q54

Keywords: Extreme precipitation risk, Stock return, Actuaries Climate Index, Asset pricing

1 Introduction

Several studies have attempted to explain the cross-sectional pattern of stock returns using aggregate risk factors such as size and book-to-market, or firm-specific risks associated with observable firm characteristics, in line with the Arbitrage Pricing Theory (APT) of Ross (1976). In recent years, climate change has become a central concern for policymakers, economists, and investors. Due to the uncertainty surrounding climate change and its potential effects on asset pricing (Barnett, 2023; Giglio et al., 2021), a rapidly growing body of literature has examined whether climate change is a potential risk factor to explain cross-sectional asset returns. There are two types of climate change risks: physical and transitional. The former refers to the adverse effects that climate and weather have on businesses, society, and supply chains (Tankov and Tantet, 2019), while the latter refers to the various possible scenarios that are coherent with a transition to a low-carbon economy (Curtin et al., 2019).

Studies in climate finance show that assets' market value may be exposed to various climate change risks, such as temperature shock (Balvers et al., 2017; Bansal et al., 2019; Cuculiza et al., 2023), drought (Hong et al., 2019), overall weather condition (Nagar and Schoenfeld, 2022), corporate carbon emission (Aswani et al., 2024a, 2024b; Bolton and Kacperczyk, 2021, 2024) and industrial pollution (Hsu et al., 2023).[1] However, extreme precipitation or rainfall conditions have not been taken into account in these studies, despite their useful insight that corporates are not immune to changing precipitation conditions. Researchers have documented that increasing air temperatures intensify rainwater cycles (Lenderink and van Meijgaard, 2008) and further cause extreme rainfall conditions that lead to an increased risk of droughts and severe floods. According to the IPCC Sixth Assessment Report (AR6), the frequency and intensity of heavy precipitation have likely increased on a global scale over a majority of land regions since 1950, and it will generally become more frequent with additional global warming (Intergovernmental Panel on Climate Change (IPCC), 2023).

[1] Venturini (2022) provides an excellent review of the research that discusses the pricing of climate risk factors in the stock market.

This study was motivated by the fact that abnormal precipitation changes have raised the level of uncertainty in economic development. Studies in climate finance have shown that extreme rainfall is directly related to corporate activities, including the deterioration of corporate water consumption (Xie and Chu, 2023), declines in corporate valuations (Rao et al., 2022), and influencing corporate risk-shifting (Aretz et al., 2019). Therefore, extreme rainfall conditions may also affect asset pricing because of the economic uncertainty associated with rainfall changes (Barnett, 2023).

We contribute to the climate finance literature by investigating whether extreme precipitation risk is priced in the cross-section of stock returns. Using US monthly data from January 1978 to November 2022 (nearly 45 years), we develop our asset pricing test in the following steps. First, we measure extreme rainfall events up to 2022 using a publicly available climate index. Our study differs from Hong et al. (2019), who use the Palmer Drought Severity Index (PDSI) to measure the relative level (intensity) of drought (precipitation). Here, we use the extreme precipitation index, a component index of the newly developed Actuaries Climate Index (ACI), to measure the extreme rainfall conditions. The extreme precipitation conditions represent the *right tail* of the distribution of rainfall conditions, as opposed to the level of precipitation. Then, at the end of each month t, we measure each firm's sensitivity to extreme precipitation (precipitation beta) and follow the standard portfolio-sort approach to create a universe of assets whose sensitivities to extreme rainfall conditions are sufficiently dispersed. If the precipitation risk factor is priced, we should see systematic differences in the average returns of our beta-sorted portfolios.

We find that the precipitation risk factor is priced in the cross-section of stock returns. Stocks with higher sensitivity to the extreme precipitation index (i.e., higher precipitation beta) exhibit higher expected returns. In particular, between January 1983 and November 2022, a spread between the returns of top and bottom deciles sorted by historical precipitation beta produces an abnormal return, i.e., alpha, of 0.156 % per year after controlling for sensitivity to market, size, value and momentum factors. Nagar and Schoenfeld (2022) find the alpha on spread between top and bottom decile portfolios sorted by overall weather beta is around 3.5 % per year. The alpha produced by precipitation beta accounts for around 5% of the alpha generated by weather beta. This result is both statistically and economically significant, and similar results occur after controlling for various risk factors and innovations in the precipitation index.

We then estimate the price of the extreme precipitation risk factor using the Fama and MacBeth (1973) method. The extreme precipitation risk factor is priced in all model specifications. The risk premium of extreme precipitation risk factor is statistically significant and positive, with magnitudes around 0.08% annually. The result may potentially provide new hedging (Engle et al., 2020) and mitigation (Azar et al., 2021) opportunities for the financial market against climate change risks.

We also contribute to the literature in climate finance that analyzes climate change risks using the climate change index. The proxy for climate change risk is an essential part of climate research. Proxies can be measured by textual analysis (Ardia et al., 2022; Engle et al., 2020; Faccini et al., 2023; Nagar and Schoenfeld, 2022), environmental, social, and governance (ESG) ratings or scores[2] (Görgen et al., 2020; Pástor et al., 2022), raw values of weather elements (Balvers et al., 2017; Bansal et al., 2019; Cuculiza et al., 2023; Ding et al., 2020), and composite climate indices (Hong et al., 2019; Jiang and Weng, 2019). The closest analysis to ours is Jiang and Weng (2019), who use the ACI index to construct their aggregate climate risk measure and create climate hedging portfolios for agricultural-related stocks. Compared with other methods, the advantage of using climate indices is that they are usually maintained by actuarial institutions and updated regularly to the public, making them easily accessible and ready for analysis (as opposed to raw climate data).

The rest of the paper is organized as follows. Section 2 describes the data for the climate index and individual stocks. Section 3 presents the asset pricing tests of precipitation risk and shows relevant empirical results. Section 4 provides additional robustness tests, and Section 5 concludes.

[2] Berg et al. (2022) provide evidence that the ESG rating provided by various data vendors is diverging. Future ESG studies should choose the data carefully since there is a possibility that the results obtained based on one ESG rating might not match those obtained from another rating agency.

2 Data

2.1 ACI and extreme precipitation index

The Actuaries Climate Index (ACI) is a composite index for monitoring various types of climate risks in the US and Canada, beginning in January 1961. It has six component indices to measure extreme climate events, including high temperatures, low temperatures, heavy rainfall, drought, high wind, and sea-level changes. Each component is presented as a standardized anomaly, and monthly and seasonal summaries are provided. A standardized anomaly is calculated by dividing the difference between the component value in a given month or season and the average value during the reference period (1961-1990) by the standard deviation of the component's values during the reference period for that month or season. The ACI data is maintained by four North American actuarial organizations and is updated every three months.[3] Apart from the country-level ACI index, there are also seven region-level indices for the US, which are consistent with those in the US National Climate Assessment. These regions include Alaska (ALA), Central East Atlantic (CEA), Central West Pacific (CWP), Midwest (MID), Southeast Atlantic (SEA), Southern Plains (SPL), and Southwest Pacific (SWP). Figure 1(a) shows the seven regions used for the ACI index, and Table 1, Panel A describes the full details of states within each region.

The extreme precipitation index is a subset of the Actuaries Climate Index, which measures the maximum rainfall over any five consecutive days, *Rx5day,* in the month relative to the reference period. Positive values of the index indicate more multiple-day, heavy precipitation events than the reference period, 1961-1990. We obtain the monthly time series of the extreme precipitation index from January 1978 to November 2022.[4] Figure 1(b) plots the time series of monthly extreme precipitation index values for the US and its seven regions. The figure illustrates that the US has experienced more extreme rainfall events since the 1980s.

[Table 1 here]

[Figure 1 here]

[3] The index is maintained by the Canadian Institute of Actuaries, the Society of Actuaries, the Casualty Actuarial Society, and the American Academy of Actuaries.
[4] The extreme precipitation index is available at https://actuariesclimateindex.org/explore/

Table 1 Panel B provides the summary statistics of the extreme precipitation index. The CWP region exhibits the highest mean values while the CEA region shows the highest max values compared to others. We also report the results of the unit root test in Table 1. There are no issues with unit roots in our monthly extreme precipitation indices. Using the augmented Dickey-Fuller (ADF) test with a time trend, we reject the null hypothesis at the 1% significance level. Therefore, our time series of extreme precipitation indices are all trend stationary.

2.2 Stock data

Our stock sample contains common shares of US firms in the three main stock exchanges (i.e., NYSE, AMEX, and NASDAQ). We select candidate stocks from the Datastream constituent lists built upon Ince and Porter (2006) and Schmidt et al. (2019) to only include common shares in our sample. First, we only keep issues listed as major securities and primary listings in case of cross-listing. Second, we select issues that are located in the domestic market and listed on domestic exchanges to exclude any firms incorporated outside the located country and not traded on the domestic exchanges. Third, we only consider equities that are neither depository receipts nor preferred equity[5]. We use equity names to search for keywords or phrases that may indicate that security is not common equity, following Campbell et al. (2010).

We then apply return screens for daily stock data to mitigate potential data bias, following methods similar to those used by Ince and Porter (2006) and Schmidt et al. (2019). We calculate daily returns of the individual stocks from price, dividends, and capital adjustment indices (CAI) to avoid the rounding problem with Datastream returns reported by Ince and Porter (2006). The CAI provides adjustments for stock splits and other capital events. The daily return is calculated from the following formula:

$$r_d = \frac{(P_d + Dividend_d) * \frac{CAI_d}{CAI_{d-1}}}{P_{d-1}} \#(1)\#$$

[5] This is similar to stocks classified as ordinary common shares in the Centre for investment research (CRSP) database (codes 10 and 11).

We then calculated the daily returns from the total return index as it contains adjustments for dividends and price by default. If the difference between the returns calculated from price data and the total return index is less than 0.01, we use the returns from the price data. If the difference exceeds 0.01, we rely on the returns from the total return index, similar to Schmidt et al. (2019). Schmidt et al. (2019) note a slight divergence between returns from the total return index and the return based on price data. Generally, price-based returns are more reliable due to improved numerical precision. However, in the case of substantial differences, the total return index may provide more reliable values.

When calculating the monthly return of stocks, we require stocks to have at least ten daily observations in the month for inclusion. Additionally, we winsorize the data at the 1st and 99th percentiles each month to mitigate the outlier and possible data errors. The monthly sample spans from the year 1978 onward, with an average of 3,643 stocks each month. The maximum number of stocks in a month reaches 4,894, while the minimum is 2,478.

3 Asset pricing tests

3.1 Baseline result

In this section, we investigate whether a stock's expected return is related to the sensitivity of its return to extreme precipitation risk. We use the values of the extreme precipitation index as the measure of this risk, as extreme precipitation conditions represent risks associated with climate change. Our approach is in line with Faccini et al. (2023) and Sautner et al. (2023), who also use the levels of their climate change risk measures to examine whether they are priced in US equities.

We employ a standard portfolio-sort approach to investigate whether extreme precipitation risk is priced. At the end of each month t, we estimate a stock's sensitivity to extreme precipitation risk by running the regression in Eq.(2) using the most recent five-year data.

$$r_{i,t} = \beta_i^0 + \beta_i^p P_t + \beta_i' F_t + \epsilon_{i,t} \#(2)$$

Where $r_{i,t}$ is the excess return of stock i at month t. P_t is the value of the extreme precipitation index in month t. F_t is a vector of selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM).

We rank stocks according to estimated precipitation betas, β_i^p, across stocks and form equal-weighted decile portfolios based on rank. Monthly excess returns of the portfolios over the next month are computed after which we roll the process by one month. This process yields a times series of 479 monthly returns for each decile portfolio, starting from January 1983. To create the spread portfolio, we long the decile 1 with a high precipitation beta and short decile 10 with a low precipitation beta. To clarify, we use the original value of the precipitation beta rather than the absolute value. As a robustness check, we also construct quintile portfolios using the same process.

After that, these portfolio returns are regressed on return-based factors commonly used in empirical asset pricing research. The regression intercepts, or alphas, explain a component of expected returns not captured by exposures to other factors. If the precipitation risk is priced, we would see large and significant differences in alphas on beta-sorted portfolios. We use the same asset pricing factors as we employed in Eq.(2) to ensure consistency.

Table 2 reports the post-ranking alphas of spread portfolios. All these alphas are significantly positive in all specifications. Specifically, the CAPM alpha is 0.156% per year (t=3.68), the Fama French three-factor alpha is 0.132% per year (t = 3.79), the four-factor alpha is 0.156% per year (t=3.72), the five-factor alpha is 0.144 % per year (t = 3.57), and six-factor alphas is 0.156% per year (t = 3.68)[6]. Harvey et al. (2016) suggest a t-statistic of 3 as a threshold for identifying new risk factors. Our results are significant even when imposing this new criterion. In most cases, our t-statistics meet or exceed this threshold, addressing concerns about data mining.

Table 2 also presents the portfolio betas with respect to the MKT, SMB, HML MOM, RMW and CMV factors. The SMB betas of the spreads portfolios are significantly positive, suggesting some tilts toward small stocks. In contrast, the HML betas of the spread portfolios are significantly negative (except for the FF5 model), suggesting some tilts towards growth stocks. The MKT, RMW, and CMA betas are insignificant, implying the risk premium associated with extreme precipitation risk is

[6] Annual alphas are computed as 12 times the monthly estimates.

independent of these factors. Therefore, small and growth stocks appear to be more exposed to extreme precipitation risk.

[Table 2 here]

3.2 Subperiod test

We conduct asset pricing tests on the spread portfolio by carrying out a subsample analysis. Studies have documented that pricing climate risk factors is a new phenomenon in the financial markets. For example, Faccini et al. (2023) find that the pricing of the US climate policy factor emerged only after 2012. We use January 2003 as a split point and investigate whether the extreme precipitation risk is priced by conducting portfolio sorts over two sub-periods: January 1983 to December 2002 and January 2003 to November 2022.

Table 3 reports sub-period results on the estimated alphas and betas and their t-statistics are reported in parentheses. We observe that the alphas of the spread portfolio sorted by the precipitation beta are both positive and statistically significant in the pre-2003 period and post-2003 period. Notably, the t-statistics of alphas in the 2003 to 2023 sub-period are more significant compared to those in the 1983 to 2002 sub-period. This result suggests that the financial markets have put more concern on pricing the extreme precipitation risk in recent years, which is possibly due to the increasing extreme precipitation events in the latter period. It implies that the pricing of physical climate risk has been priced since the 1980s, which contrasts to the findings of Faccini et al. (2023) that climate transition risk has been priced only in recent years.

[Table 3 here]

3.3 Fama Macbeth regression

The portfolio sort approach provides evidence that the precipitation risk is priced in the cross-section of US equity returns. We perform a further robustness test by conducting Fama-MacBeth (1973) (FM) regressions over the full period. This approach allows us to directly estimate the risk premium of the extreme precipitation risk factor by constructing a portfolio with a unit beta of for the tested risk factor and zero betas for all other factors.

We conduct cross-sectional regression tests for individual stocks using the Fama and MacBeth (1973) methodology with a five-year rolling window. In the first-step regressions, betas are estimated over the past five-year periods for each stock at the end of each month t using Eq. (3). The procedure is repeated at the end of each month.

$$r_{i,t} = \beta_i^0 + \beta_i^p P_t^S + \beta_i' F_t + \epsilon_{i,t} \#(3)$$

F_t is a vector that includes risk factors that have been found to explain the cross-section stock returns and β_i is a vector that contains the factor loading for these factors. P_t^S is the monthly returns of the decile spread portfolio, thus, the traded precipitation risk factor. For simplicity, we use the traded precipitation risk factor obtained from Eq. (2), after controlling for Fama-French-Carhart four factors.

In the second step, these betas are used in the cross-sectional regression in Eq. (4) to obtain the price of extreme precipitation risk.

$$r_{i,t} = \gamma_0 + \gamma_t^p \beta_i^p + \gamma'_t \beta_i + u_i \#(4)$$

We calculate the average coefficients of betas and correct their standard errors for the bias using Newey and West (1987) standard errors.

Table 4 presents the results of cross-sectional regression using various risk factors. The base model includes betas of the extreme precipitation and market factors, while other specifications control for size, value, momentum, investment and profitability factors. The CAPM model shows that the monthly average coefficient of extreme precipitation risk factor is statistically significant at a 5% level, with a magnitude of 0.007% (0.084% per year). The significance of precipitation risk factors persists when controlling for other risk factors. The monthly average coefficients on the precipitation risk factor are around 0.007% to 0.008%, which is approximately equal to 0.084% to 0.096% per year. All coefficients of the extreme precipitation risk factor are statistically significant at the 1% level. Therefore, the FM regressions confirm the results from the portfolio sorts analysis that the extreme precipitation risk is priced in the cross-section of stock returns.

Overall, the evidence strongly supports our hypothesis that extreme precipitation risk factor is priced. The premium for this risk is positive, indicating that stocks with higher sensitivity to extreme precipitation risk offer higher expected returns. This result is consistent with the notion that the risk-neutral investor perceives rises in extreme precipitation as undesirable, thus requiring compensation for holding stocks with greater exposure to this risk.

[Table 4 here]

3.4 Size and value portfolios

In section 3.1, we observe that small or growth firms exhibit greater sensitivity to the extreme precipitation risk. In this section, we aim to test the hypothesis that firms that are more sensitive to extreme precipitation risk demonstrate higher loadings on the precipitation risk factor, P_t^S . We anticipate that small firms or growth firms show higher loadings to the precipitation risk factor than larger or value firms since these firms may have fewer resources to adapt or adjust.

To test our hypothesis, we utilize Fama-French 25 value-weighted portfolios formed based on size and book-to-market (BM). The factor loadings of the portfolios are inferred from the following:

$$r_{i,t} = \alpha_0 + \beta_i^M MKT_t + \beta_i^p P_t^S + \epsilon_{i,t} \#(5)$$

Where P_t^S is the monthly returns of the decile spread portfolio, thus, the traded precipitation risk factor. The precipitation risk factor is obtained from Eq. (2) after controlling for Fama-French-Carhart four factors.

Table 5 reports the results for the 25 size- and BM-sorted portfolios. Those results are consistent with our expectations. For instance, the precipitation factor loadings of the small-growth portfolio and small-value portfolio are 14.779 and 4.073, respectively, suggesting that growth firms have higher loading to the precipitation risk factor. Similarly, the precipitation loadings of the small-value portfolios and the big-value portfolio are 4.073 and -3.427, respectively, implying that small firms have higher loading to the precipitation risk factor.

To further test our hypothesis, we create equal-weighted portfolios to capture the average sensitivities of stocks. "SMALL" includes five portfolios with small capitalizations, while "BIG" contains five portfolios with large capitalizations; "VALUE" includes five value portfolios, and "GROWTH" contains five growth portfolios. "SMALL - BIG" measures the difference in returns between small and large portfolios, whereas "VALUE - GROWTH" measures the difference in returns between value and growth portfolios. These results are also reported in Table 5.

The loading on the extreme precipitation risk factor for the portfolio of small stocks is 42.578 (t=3.73), while for the portfolio of big stocks is -16.194 (t=-3.47). The beta for the difference between small and big portfolios (SMALL-BIG) is 58.807, with a t-statistic of 4.31. The beta on the extreme precipitation risk factor for the growth portfolio is 32.836 (t=4.06), while that for the portfolio of value stocks is -5.622 (t =-0.62). The beta for the difference between value and growth portfolios (VALUE-GROWTH) is −38.423 with a t-statistic of −3.19. We also test our hypothesis using 25 equal-weighted portfolios formed on size and book-to-market (BM). These results are similar to the value-weighted portfolios and upon request.

These findings strongly support our hypothesis that firms that are more sensitive to extreme precipitation risk exhibit higher loadings on the extreme precipitation risk factor.

[Table 5 here]

3.5 Regional-level extreme precipitation risk

In this section, we apply the same sets of asset pricing tests in Section 3.1 using the six regional extreme precipitation indices in the US. We hypothesize that regional extreme precipitation would be less priced in the stock returns since regional extreme precipitation risk could be spatially diversified. For example, firms could locate facilities in regions less prone to extreme or invest in in infrastructure such as enhanced drainage systems, flood defences, and weather-resistant materials to mitigate potential damages to reduce their direct exposure. Additionally, firms can diversify operations across multiple regions to spread the risk.

[Table 6 here]

Table 6 reports the alphas of the decile spread portfolio for six regions: Alaska (ALA), Central East Atlantic (CEA), Central West Pacific (CWP), Midwest (MID), Southeast Atlantic (SEA), Southern Plains (SPL), and Southwest Pacific (SWP). We observe less significant alphas for the spread portfolio in regional extreme precipitation indices compared to the country-level index. Specifically, only the SWP region shows a statistically significant alpha at a 1% significance level in FF5 and FF6 models, with t-statistics less than 3, a hurdle suggested by Harvey et al. (2016). Some significant alphas at the 5% level are observed in the MID, SEA, and SPL regions in some specifications, with statistics less than 3. These results confirm that regional extreme precipitation events can be spatially diversified to some extent.

In previous sections, we find strong evidence of the pricing of extreme precipitation risk at the country level, as extreme precipitation can have widespread impacts beyond local facilities. It disrupts supply chains, affects raw materials and transportation networks, and leads to delays and increased costs, which cascade through production and distribution processes. These disruptions make country-level extreme precipitation a significant, undiversifiable risk factor for firms. In other words, country-level extreme precipitation represents a systematic, spatially undiversifiable risk factor.

4 Additional robustness test

4.1 Alternative precipitation risk specification

In Section 3, we use the level of extreme precipitation rather than the innovation of extreme precipitation risk to conduct our asset pricing test. As a robustness test, we explore using innovation in precipitation to construct a systematic climate risk factor. We employ the AR (2) model to construct unanticipated innovations in precipitation, similar to Pastor and Stambaugh (2003). We also add a deterministic trend to capture the long-term effect of climate change in the country, as suggested by Hong et al. (2019)[7].

$$P_t = a_i + b_i t + c_i P_{i,t-1} + d_i P_{t-2} + u_{i,t} \# (6)$$

[7] Hong et al. (2019) specify an AR (1) model with a deterministic trend when using the climate index:

$$Index = a_i + b_i t + c_i Index_{i,t-1} + \epsilon_{i,t}$$

The term (b_i) captures the long effect of climate change on the country.

The fitted residuals, $u_{i,t}$, is the innovation in precipitation, which captures unanticipated extreme precipitation risk.

We calculate stocks' sensitivity to innovation in precipitation by regressing stocks' excess return on innovations in precipitation and other risk factors:

$$r_{i,t} = \beta_i^0 + \beta_i^p P_t^I + \beta_i' F_t + \epsilon_{i,t} \# (7)$$

Where P_t^I is the innovation in precipitation, which is equal to $u_{i,t}$ in Eq. (6).

We repeat the portfolio sorting approach to construct decile and quintile portfolios as described in Section 3.1, and we use the same asset pricing factors as we employed in Eq.(7) to compute decile and quintile portfolio alphas.

Table 7 reports the equal-weighted decile portfolio alphas and other factor loadings (betas), structured similarly to Table 1. We find all alphas of the spread portfolios are significantly positive across all specifications. The four-factor alpha is 0.144% per year (t=3.34), and the five-factor alpha is 0.132% per year (t = 3.29). Moreover, consistent patterns show that small and growth stocks exhibit higher exposure to extreme precipitation risk. SMB betas are significantly positive for decile spread portfolios, while the HML betas are significantly negative. Our results suggest that our results are not sensitive to the specification of precipitation risk.

[Table 7 here]

4.2 Alternative portfolio size

In section 3, we construct the extreme precipitation risk factor using the decile portfolios. To make sure our result is not driven by the size of the portfolios, we consider using the quintile portfolios to conduct the asset pricing test as a robustness test. We follow the beta-sorting process described in Section 3.1 to form quintile spread portfolios by calculating the difference between the monthly returns of Quintile 1 and Quintile 5. We then regress the monthly return of the spread portfolio on the same set of factors that measure the stocks' sensitivity to extreme precipitation risk.

Table 8 reports the results of the quintile spread portfolio alphas and other factor loadings (betas) across five performance models. All these alphas are significantly positive across all specifications. Those alphas are quantitatively similar, around 0.108%

per year. Not surprisingly, compared with decile spread portfolios, the magnitudes of alphas (and their t-statistics) for quintile portfolios are slightly smaller. However, in all models, the t-statistics of alphas still exceed the threshold of three suggested by Harvey et al. (2016). Furthermore, we observe consistent patterns that small and growth stocks show more exposure to extreme precipitation risk. The SMB betas are all significantly positive, while the HML betas are significantly negative.

[Table 8 here]

5 Conclusion

Using the extreme precipitation index, we construct an extreme precipitation risk mimicking portfolio by taking long positions in the top decile with higher precipitation beta and short positions in the bottom decile with lower precipitation beta. This approach allows us to assess whether extreme precipitation risk is a new systematic risk factor. Our paper focuses on systematic extreme precipitation risk in stock returns and concludes that stocks more exposed to country-wide extreme precipitation fluctuations command higher expected returns. Thus, the extreme precipitation risk is priced in the cross-section of stock returns. This result holds when using quantile portfolios, alternative specifications of precipitation and different factor models. Moreover, this pricing has appeared to be a long-term phenomenon since the 1980s, with stronger evidence emerging in recent periods. Our results align with Balvers et al. (2017), Bansal et al. (2019) and Nagar and Schoenfeld (2022), who similarly find that risks associated with physical climate are priced in financial markets as additional risk factors.

Our findings have several implications for academics, policymakers and practitioners. First, we assess the price of risk associated with the extreme precipitation risk factor using the two-step Fama and Macbeth (1973) procedure. We identify consistent small risk premiums and this may provide new hedging opportunities for investors. Second, our results validate regulatory concerns about climate risks and advocate further exploration of the corporate disclosure of climate risk exposure. Third, our findings show climate index might be a very useful tool for forming portfolios and managing risks, thereby prompting further research in this area.

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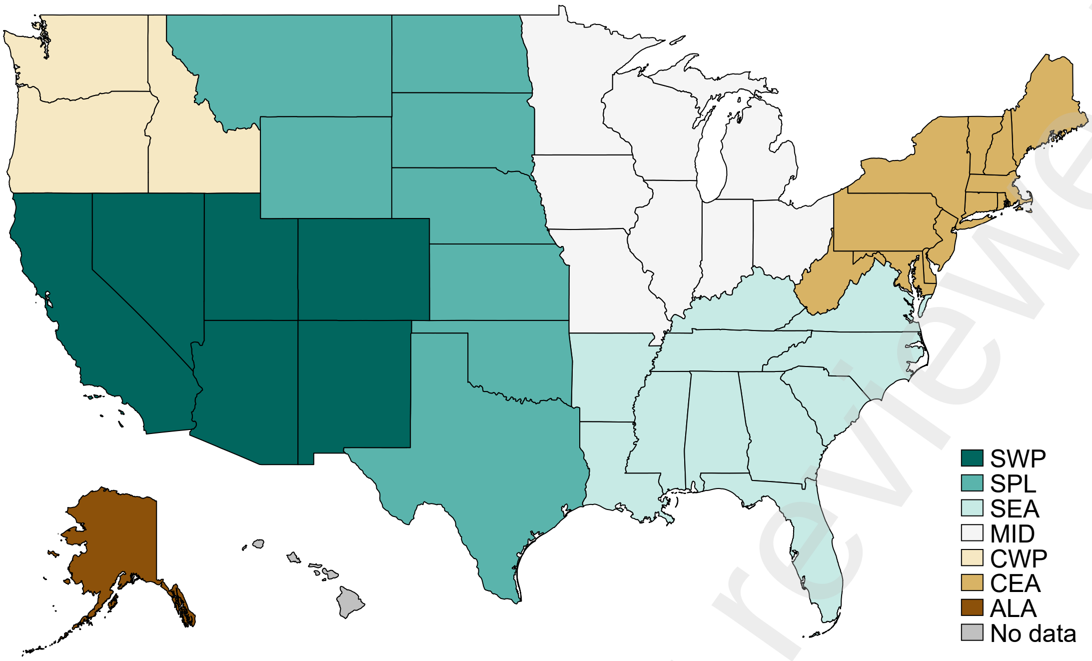

Firgure 1(a)

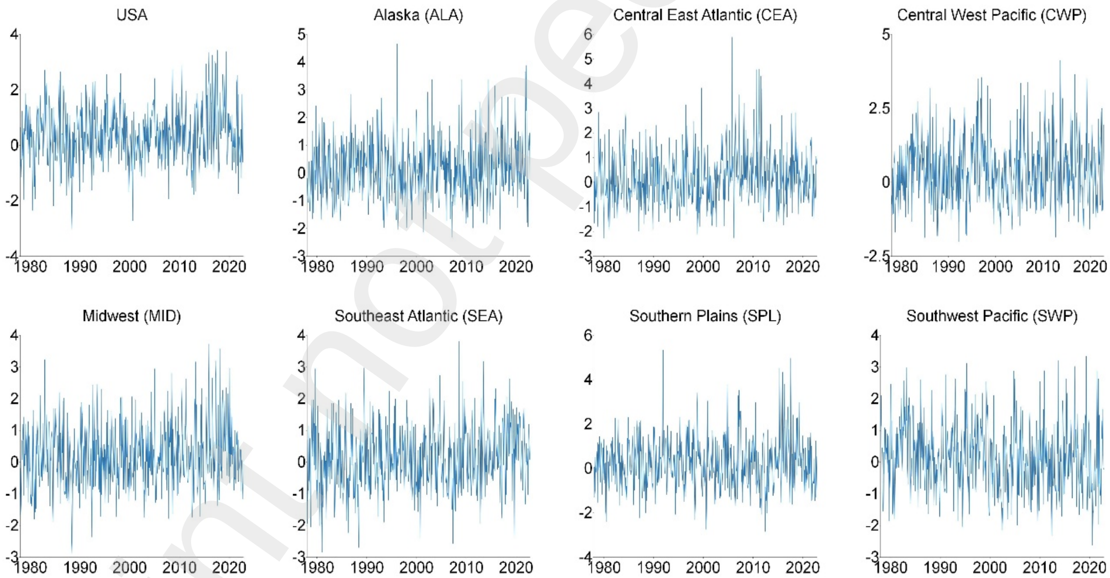

Figure 1 (b)

Figure 1 The extreme precipitation index.

Table 1 Summary statistics of the extreme precipitation index

Panel A provides a detailed description of regions included in the extreme precipitation index (excluding Hawaii due to its small size). Panel B presents the number of monthly observations, mean, standard deviation, minimum, and maximum values. We also provide the result of the Augmented Dickey-Fuller (ADF) test with time trend (p-values are reported).

Panel A

Region	Description	States
USA	United States	All states
ALA	Alaska	AK
CEA	Central East Atlantic	CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, VT, WV
CWP	Central West Pacific	ID, OR, WA
MID	Midwest	IA, IL, IN, MI, MN, MO, OH, WI
SEA	Southeast Atlantic	AL, AR, FL, GA, KY, LA, MS, NC, SC, TN, VA
SPL	Southern Plains	KS, MT, ND, NE, OK, SD, TX, WY
SWP	Southwest Pacific	AZ, CA, CO, NM, NV, UT

Panel B

Region	Obs	Mean	Std	Min	Max	ADF
USA	539	0.38	1.01	-3.02	3.42	0.00
ALA	539	0.14	1.08	-2.32	4.66	0.00
CEA	539	0.20	1.12	-2.27	5.88	0.00
CWP	539	0.40	1.09	-2.01	4.12	0.00
MID	539	0.21	1.01	-2.86	3.72	0.00
SEA	539	0.12	1.01	-2.84	3.81	0.00
SPL	539	0.26	1.15	-2.84	5.33	0.00
SWP	539	0.15	1.07	-2.61	3.34	0.00

Table 2 Factor loadings of decile portfolio returns sorted on the sensitivity to precipitation

At the end of month t, we estimate a stock's sensitivity to extreme precipitation (precipitation beta) over the recent five years controlling for selected risk factors, $r_{i,t} = \beta_i^0 + \beta_i^p P_t + \beta_i' F_t + \epsilon_{i,t}$, where P_t is the value of the extreme precipitation index in month t and F_t denotes selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). We estimate the precipitation beta using five performance models, including the CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4), Fama-French 5-factor model (FF5), and Fama-French-Momentum 6-factor model (FF6). Based on the precipitation beta, stocks are sorted into equal-weighted decile portfolios. The monthly returns of these decile portfolios over the next month are computed after which we repeat the process. The return of the spread portfolio is the difference between the top decile (decile 1) with a high precipitation beta and the bottom decile (decile 10) with a low precipitation beta. Finally, the monthly returns of these portfolios are regressed on the same set of risk factors. Newey-West standard errors are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

	CAPM	FF3	FF4	FF5	FF6
ALPHA	0.013***	0.011***	0.013***	0.012***	0.013***
	(3.68)	(3.79)	(3.72)	(3.57)	(3.68)
MKT	-0.001	-0.001	-0.001	-0.003**	-0.003***
	(-0.56)	(-0.92)	(-1.37)	(-2.51)	(-3.23)
SMB		0.003**	0.003**	0.003*	0.003*
		(2.08)	(2.52)	(1.97)	(1.93)
HML		-0.003*	-0.003*	-0.003	-0.005**
		(-1.81)	(-1.93)	(-1.50)	(-2.42)
MOM			-0.002		-0.002
			(-1.18)		(-0.96)
RMW				0.000	0.001
				(0.18)	(0.43)
CMA				-0.003	-0.001
				(-0.76)	(-0.35)

Table 3 Portfolio sort analysis over subsamples

At the end of month t, we estimate a stock's sensitivity to precipitation (precipitation beta) over the recent five years controlling for selected risk factors, $r_{i,t} = \beta_i^0 + \beta_i^p P_t + \beta_i' F_t + \epsilon_{i,t}$, where P_t is the value of the extreme precipitation index in month t and F_t denotes selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). We estimate the precipitation beta using five performance models, including CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4), Fama-French 5-factor model (FF5), and Fama-French-Momentum 6-factor model(FF6). Based on the precipitation beta, stocks are sorted into equal-weighted decile portfolios. The monthly returns of these decile portfolios over the next month are computed after which we repeat the process. The return of the spread portfolio is the difference between the top decile (decile 1) with a high precipitation beta and the bottom decile (decile 10) with a low precipitation beta. We divide the monthly return of the spread portfolio into two sub-samples, January 1983 to December 2002 and January 2003 to November 2022. Finally, the monthly returns of spread portfolios are regressed on the same set of risk factors. Newey-West standard errors are reported in parentheses. ***, **, and * indicate statistical significance (two-tail test) at the 1%, 5%, and 10% levels, respectively.

Panel A	1983-2002				
	CAPM	FF3	FF4	FF5	FF6
ALPHA	0.013**	0.012**	0.015**	0.014**	0.015**
	(2.57)	(2.40)	(2.19)	(2.31)	(2.10)
MKT	-0.000	-0.000	-0.000	-0.003	-0.002
	(-0.22)	(-0.15)	(-0.27)	(-1.54)	(-1.49)
SMB		0.003*	0.004**	0.005**	0.005**
		(1.69)	(2.22)	(1.99)	(2.39)
HML		-0.002	-0.002	-0.002	-0.002
		(-0.75)	(-0.66)	(-0.57)	(-0.45)
MOM			-0.002		-0.001
			(-0.67)		(-0.45)
RMW				0.000	0.001
				(0.17)	(0.25)
CMA				-0.004	-0.004
				(-0.66)	(-0.78)

Panel B	2003-2022				
	CAPM	FF3	FF4	FF5	FF6
ALPHA	0.013**	0.010***	0.010***	0.010***	0.010***
	(2.56)	(2.71)	(2.80)	(2.80)	(3.13)
MKT	-0.001	-0.001	-0.002**	-0.002*	-0.004***
	(-0.53)	(-1.10)	(-2.03)	(-1.82)	(-3.88)
SMB		0.003**	0.003*	0.001	0.000
		(2.13)	(1.96)	(0.34)	(0.11)
HML		-0.003	-0.004**	-0.002	-0.007***
		(-1.57)	(-2.20)	(-1.06)	(-2.72)
MOM			-0.003**		-0.003**
			(-2.22)		(-2.34)
RMW				0.000	0.000
				(0.09)	(0.22)
CMA				-0.001	0.001
				(-0.48)	(0.43)

Table 4 Fama and Macbeth regression

We use the Fama and MacBeth (1973) methodology with a 5-year rolling window to test the pricing of the extreme precipitation risk factor. In the first step, betas are estimated over the past five-year periods for each stock at the end of month t and we repeat the procedure by rolling the beta estimation window forward by one month. $r_{i,t} = \beta_i^0 + \beta_i^p P_t^S + \beta_i' F_t + \epsilon_{i,t}$, where F_t denotes selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). P_t^S is the monthly returns of the decile spread portfolio, thus, the traded extreme precipitation risk factor. We estimate the betas using five performance models, including the CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4), Fama-French 5-factor model (FF5), and Fama-French-Momentum 6-factor model (FF6). In the second step, these betas are used in the cross-sectional regression to obtain the price of the extreme precipitation risk factor. $r_{i,t} = \gamma_0 + \gamma_t^p \beta_i^p + \gamma_t' \beta_i + u_i$. We calculate the average coefficients of betas and correct their standard errors for the bias using New and West standard errors (reported in parentheses). ***, **, and * indicate statistical significance (two-tail test) at the 1%, 5%, and 10% levels, respectively.

	CAPM	FF3	FF4	FF5	FF6
ALPHA	-0.201***	-0.210***	-0.210***	-0.212***	-0.212***
	(-11.04)	(-11.64)	(-11.68)	(-11.74)	(-11.80)
P_t^S	0.007**	0.007**	0.008**	0.007**	0.008**
	(2.00)	(2.31)	(2.43)	(2.21)	(2.47)
MKT	-0.036	-0.076	-0.061	-0.103	-0.085
	(-0.16)	(-0.37)	(-0.30)	(-0.51)	(-0.42)
SMB		0.186	0.164	0.188	0.174
		(1.30)	(1.15)	(1.36)	(1.25)
HML		0.075	0.078	0.097	0.083
		(0.45)	(0.47)	(0.60)	(0.51)
MOM			-0.233		-0.190
			(-1.13)		(-0.93)
RMW				-0.017	-0.004
				(-0.14)	(-0.03)
CMA				0.096	0.075
				(1.02)	(0.81)

Table 5 Factor loadings of size and value sorted portfolios

The factor loadings of 25 size-value sorted (value-weighted) portfolios are estimated from: $r_{i,t} = \alpha_0 + \beta_i^M MKT_t + \beta_i^p P_t^S + \epsilon_{i,t}.$, where P_t^S is the monthly returns of the decile spread portfolio, thus, the traded precipitation risk factor. We use the extreme precipitation risk factor obtained from Eq. (2), after controlling for Fama-French-Carhart four factors. In addition to standard 25 size-value sorted portfolios, we create equal-weighted portfolios to capture the average sensitivities of stocks. "SMALL" includes five portfolios with small capitalizations, while "BIG" contains five portfolios with large capitalizations; "VALUE" includes five value portfolios, and "GROWTH" contains five growth portfolios. "SMALL - BIG" measures the difference between small and large portfolios, whereas "VALUE - GROWTH" measures the difference between value and growth portfolios. ***, **, and * indicate statistical significance (two-tail test) at the 1%, 5%, and 10% levels, respectively.

Size	BM	Alpha	MKT	P_t^S	R^2
Small	Growth	-0.998***	1.354***	14.779***	0.61
	2	-0.150	1.173***	9.939***	0.60
	3	-0.069	1.042***	7.332***	0.68
	4	0.221	0.978***	6.596***	0.62
	Value	0.328*	1.008***	4.073	0.56
2	Growth	-0.477***	1.335***	7.591***	0.72
	2	-0.016	1.135***	4.560**	0.75
	3	0.142	1.025***	0.888	0.75
	4	0.186	0.982***	0.748	0.71
	Value	0.172	1.133***	-0.771	0.67
3	Growth	-0.345**	1.269***	6.100***	0.77
	2	0.109	1.098***	1.183	0.82
	3	0.118	0.980***	-3.062**	0.79
	4	0.256**	0.994***	-3.885**	0.74
	Value	0.304*	1.059***	-2.625	0.67
4	Growth	-0.057	1.179***	3.335**	0.82
	2	0.106	1.052***	-1.977*	0.87
	3	0.101	1.010***	-2.550*	0.81
	4	0.187*	0.981***	-4.096***	0.77
	Value	0.203	1.053***	-2.729	0.68
Big	Growth	0.070	0.987***	1.174	0.90
	2	0.121	0.918***	-1.831*	0.87
	3	0.182*	0.873***	-4.147***	0.80
	4	0.020	0.916***	-7.818***	0.69
	Value	0.120	1.038***	-3.427	0.60
SAMLL		0.450	5.549***	42.578***	0.67
BIG		1.630***	4.726***	-16.194***	0.90
VALUE		2.245***	5.285***	-5.622	0.74
GROWTH		-0.688	6.117***	32.836***	0.83
SMALL-BIG		-1.460	0.825***	58.807***	0.06
VALUE- GROWTH		2.654***	-0.831***	-38.423***	0.06

Table 6 Alphas of decile portfolio returns sorted on the sensitivity to regional precipitation index

At the end of month t, we estimate a stock's sensitivity to regional extreme precipitation (precipitation beta) over the recent five years controlling for selected risk factors, $r_{i,t} = \beta_i^0 + \beta_i^p P_t + \beta_i' F_t + \epsilon_{i,t}$, where P_t is the value of the regional extreme precipitation index in month t and F_t denotes selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). These regions include Alaska (ALA), Central East Atlantic (CEA), Central West Pacific (CWP), Midwest (MID), Southeast Atlantic (SEA), Southern Plains (SPL), and Southwest Pacific (SWP).

We estimate the precipitation beta using five performance models, including the CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4), Fama-French 5-factor model (FF5), and Fama-French-Momentum 6-factor model (FF6). Based on the precipitation beta, stocks are sorted into equal-weighted decile portfolios. The monthly returns of these decile portfolios over the next month are computed after which we repeat the process. The return of the spread portfolio is the difference between the top decile (decile 1) with a high precipitation beta and the bottom decile (decile 10) with a low precipitation beta. Finally, the monthly returns of these portfolios are regressed on the same set of risk factors. Newey-West standard errors are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

	CAPM	FF3	FF4	FF5	FF6
ALA	0.004	-0.001	-0.001	0.002	0.002
	(1.05)	(-0.34)	(-0.35)	(0.75)	(0.57)
CEA	0.004	0.006*	0.007**	0.003	0.003
	(1.00)	(1.73)	(1.96)	(0.74)	(0.80)
CWP	0.007*	0.006*	0.004	0.006*	0.005
	(1.66)	(1.75)	(1.21)	(1.82)	(1.24)
MID	0.005	0.008**	0.008**	0.009***	0.010***
	(1.14)	(2.54)	(2.56)	(2.60)	(2.99)
SEA	0.006	0.010**	0.010**	0.006	0.006
	(1.29)	(2.40)	(2.51)	(1.62)	(1.52)
SPL	0.003	0.001	0.001	-0.000	0.000
	(0.81)	(0.33)	(0.39)	(-0.05)	(0.10)
SWP	0.007*	0.007*	0.006	0.012***	0.010***
	(1.88)	(1.83)	(1.62)	(3.38)	(3.31)

Table 7 Factor loadings of decile portfolio returns sorted on the sensitivity to innovation in precipitation.

At the end of month t, we estimate a stock's sensitivity to innovation in precipitation (precipitation beta) over the recent five years controlling for selected risk factors. $r_{i,t} = \beta_i^0 + \beta_i^p P_t^I + \ + \beta_i' F_t + \epsilon_{i,t}$, where P_t^I is the innovation in extreme precipitation in month t and and F_t denotes selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). We estimate the precipitation beta using five performance models, including the CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4), Fama-French 5-factor model (FF5), and Fama-French-Momentum 6-factor model (FF6).
Based on the precipitation beta, stocks are sorted into equal-weighted decile portfolios. The monthly returns of these decile portfolios over the next month are computed after which we repeat the process. The return of the spread portfolio is the difference between the top decile (decile 1) with a high precipitation beta and the bottom decile (decile 10) with a low precipitation beta. Finally, the monthly returns of these portfolios are regressed on the same set of risk factors. Newey-West standard errors are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

	CAPM	FF3	FF4	FF5	FF6
ALPHA	0.013***	0.011***	0.011***	0.012***	0.011***
	(3.94)	(3.76)	(3.34)	(3.29)	(3.16)
MKT	-0.000	-0.001	-0.001	-0.003**	-0.003***
	(-0.37)	(-1.26)	(-1.17)	(-2.79)	(-2.83)
SMB		0.003**	0.003**	0.003	0.002
		(2.21)	(2.56)	(1.62)	(1.45)
HML		-0.002*	-0.003*	-0.004**	-0.005**
		(-1.98)	(-1.94)	(-2.08)	(-2.49)
MOM			-0.001		-0.002
			(-0.94)		(-1.14)
RMW				0.001	0.001
				(0.40)	(0.46)
CMA				-0.002	-0.000
				(-0.51)	(-0.08)

Table 8 Factor loadings of quintile portfolio returns sorted on the sensitivity to precipitation

At the end of month t, we estimate a stock's sensitivity to extreme precipitation (precipitation beta) over the recent five years controlling for selected risk factors, $r_{i,t} = \beta_i^0 + \beta_i^p P_t + \beta_i' F_t + \epsilon_{i,t}$, where P_t is the value of the extreme precipitation index in month t and F_t denotes selected risk factors in asset pricing models, including market risk (MKT), size (SMB), value (HML), profitability (RMW), investment (CMA) and momentum (MOM). We estimate the precipitation beta using five performance models, including the CAPM, Fama-French 3-factor model (FF3), Fama-French-Carhart 4-factor model (FF4), Fama-French 5-factor model (FF5), and Fama-French-Momentum 6-factor model (FF6). Based on the precipitation beta, stocks are sorted into equal-weighted quintile portfolios. The monthly returns of these decile portfolios over the next month are computed after which we repeat the process. The return of the spread portfolio is the difference between the top quintile (quintile 1) with high precipitation beta and the bottom quintile (quintile 5) with low precipitation beta. Finally, the monthly returns of these portfolios are regressed on the same set of risk factors. Newey-West standard errors are reported in parentheses. ***, **, and * indicate statistical significance (two-tailed test) at the 1%, 5%, and 10% levels, respectively.

	CAPM	FF3	FF4	FF5	FF6
ALPHA	0.009***	0.009***	0.009***	0.009***	0.009***
	(3.27)	(3.78)	(3.25)	(3.56)	(3.06)
MKT	0.000	-0.000	-0.001	-0.002**	-0.002***
	(0.30)	(-0.37)	(-0.70)	(-2.58)	(-2.93)
SMB		0.003***	0.003***	0.002	0.002
		(3.59)	(3.70)	(1.31)	(1.36)
HML		-0.000*	-0.001	-0.001	-0.003*
		(-1.65)	(-1.26)	(-0.682)	(-1.78)
MOM			-0.001		-0.001
			(-0.99)		(-1.08)
RMW				-0.000	0.000
				(-0.11)	(0.04)
CMA				-0.002	-0.001
				(-1.11)	(-0.53)