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The extreme temperature factor in asset pricing models: Evidence from Europe

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ABSTRACT

Growing concern about climate change has led to increased research into the effects of climate on markets. One of the weather variables studied is temperature. The previous studies considered that the temperature influences on asset returns through changes in investor mood. There are few studies that incorporate a risk factor to analyze the effects of temperature changes on asset returns. We extract positive and negative extreme temperature changes to design three temperature factors. By a cross-section asset pricing model, we find evidence that temperature shocks (hot and cold) show a significant monthly risk premium and skewness for temperature changes.

1. Introduction

There is a vast literature that analyzes the influence of investor sentiment on asset returns. This field of research is known as behavioral finance and within this one there is a multitude of empirical works that study how mood affects asset market prices. Within this field, we find studies that analyze the effects of weather variables on investor mood and how this affects the behavior of market prices. In this line, Saunders (1993) is the first empirical work that relates weather to stock return. He shows that there is a negative relationship between cloudy periods and return. Similarly, Kamstra et al. (2003) observed that periods with longer nights (winter) show lower stock returns, thus coining the term *sunshine* effect.

However, for the purposes of the field of our study, Cao and Wei (2005) is the first empirical work that relates daily temperature with daily stock returns and found a negative relationship between both variables. The explanation was found in the change in investor mood and apathy, so this study is situated within behavioral finance since its testing is carried out using an autoregressive model of order 1 of asset returns in which the average daily temperature, estimated from the maximum and minimum, is also included as an explanatory variable. Therefore, it is not an asset valuation model per se.

Subsequently, Keef et al. (2007) also found a negative relationship between temperature and the performance of Australian stock indexes, but they also showed that this relationship is stronger for seasonally adjusted temperature than for the average daily temperature level. In this case, the methodology used does not correspond to an asset pricing model either.

Floros (2008) analyzed this relationship between temperature and stock returns in Europe, and found that the relationship is negative and significant for some of the countries, but curiously for the warmest country in the sample (Greece) and one of the coldest (United Kingdom), the relationship is not significant. As for the methodology used, it follows the usual line, but adds a

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GARCH process to adjust the residuals of the daily returns and thus explain the stylized fact and fat tails of the daily asset returns, although it is still not an asset pricing model strictly speaking.

Contrary to the above, Jacobsen and Marquering (2008), using monthly data, concluded that the relationship between weather and asset returns could be spurious and that it does not appear to be a causal relationship resulting from a change in investor mood, but rather a consequence of the winter-summer difference, which could only represent a change in activity and consumption levels.

Symeonidis et al. (2010) analyzed the relationship between different weather variables and some measures of asset return volatility. Their results, although they do not correspond to an asset pricing model either, show two relevant issues: on the one hand, they confirm the evidence found in other works that assume that the effects of temperature are different depending on the time of the year and geographical location; and on the other hand, they add new evidence regarding the different effect depending on whether the temperature is extreme positive, extreme negative or considered at usual average levels for the time of the year.

Lu and Chou (2012) is an empirical study that advances methodologically in two aspects: the number of variables analyzed (yield, turnover, volatility and liquidity); and the frequency of observation of the data (intraday). Its results with respect to temperature only show a significant relationship with turnover (positive) and with illiquidity (negative), but not with asset returns although, as in previous studies, the model used is not an asset pricing model.

Bourdeau-Briena and Kryzanowski (2017) fitted ARMAX-GARCH models to analyze the effect of geographically localized extreme weather events on asset returns. For extreme temperatures they do not find a contemporaneous relationship, although they do find a lagged (causal) relationship in some US states.

Balvers et al. (2017) is the first paper to use an asset pricing model (CAPM of Markowitz (1952) and factorial model of Fama and French (1993)) to test the effect of temperature on asset returns; in addition, they extract an explanatory factor of temperature defined as the unexpected change for a seasonal temperature model. Their results are in line with the ones above, as they find a negative relationship between temperature shock and asset returns. However, its conclusions must be taken with caution since: first, the temperature shock is a variable,[1] and not a factor with observable market value unlike the other factors (market, SMB, HML, among others) which are represented by portfolios of traded assets; second, the temperature data are analyzed on a monthly frequency; third, the temperature factor is the residual of a seasonal model but does not differentiate extreme situations from the usual temperatures; and finally it should be noted that the model is tested on industrial portfolios and not on assets.

Choi et al. (2020) analyzes, among other questions, whether extreme temperatures have any effect on asset returns. For this purpose, he defines extreme temperatures based on the values exceeding the mean value of the last five years and the mean deviations of the last 10, but his study is performed with monthly data. Although their study does not assume any asset pricing model (it uses a panel data model) they find that such extreme temperatures have a negative relationship on the monthly return of asset portfolios. Finally, Venturini (2022) provides a good review of the literature on the relationship between climate and asset returns.

In summary, the literature shows that extreme temperature has a negative relationship with stock returns, both in daily and monthly frequency and that this relationship depends on the geographical area; except for Balvers et al. (2017), the rest of the empirical studies analyze the relationship between temperature and return, but do not look for the corresponding risk premium, since they do not use an asset pricing model. Despite the above, Balvers et al. (2017) does not use daily data and more importantly, the temperature factor is a portfolio formed by those assets that best explain the behavior of temperature, i.e., unlike the rest of the factors (see Fama and French (1993)) it is not the difference between the returns that the assets that perform better in the face of the factor (extreme temperature) and those that perform worse; therefore, although the model includes the usual asset pricing factors, if a new factor (temperature) is introduced that is not constructed in a similar way to the rest it is difficult to draw conclusions regarding risk premia.

In addition, there is a growing demand from investors to include weather variables in their decision making and it seems that to date the market has only responded by means of portfolios composed of companies that meet certain regulatory criteria; also, in the financial sector an active management of weather risk is demanded. In this context, we did not find a quantitative answer in the literature to estimate risk premiums in the face of shocks in weather variables, in particular, we find that there is a gap in the literature that studies whether extreme temperatures are really a factor that intervenes in asset pricing or, on the contrary, is a variable that is already included in the rest of the factors commonly used; this is therefore our aim i.e., to show a methodology for estimating risk premiums for weather shocks (temperature), allowing investors to manage their portfolios according to the sensitivity of companies to weather risk and not on the basis of compliance with certain regulatory requirements that are difficult to assess quantitatively, as well as allowing financial institutions to adequately value their operations according to the weather sensitivity of their counterparties.

The rest of the paper is organized as follows: Section 2 describes the methodology followed for the study. Section 3 describes the data used; Section 4 shows the results obtained and ends with the main conclusions drawn from the study.

[1] See equation-4 in Balvers et al. (2017) where the risk factor is defined as a mimicking portfolio of excess returns of those assets whose linear combination best explains the temperature shock, but not how extreme temperature influences asset returns.

2. Methodology for analyzing the temperature factor in asset princing models

2.1. Temperature variable definition

Our methodology begins with the definition of the temperature variable, for which we follow the literature on the valuation of weather derivatives (see Dupuis (2011)).

Financial contracts on weather products have been traded on organized markets for some years now. For example, the Chicago Mercantile Exchange trades derivative contracts on the temperature of some of the world's cities. Specifically, the degrees above (heating, HDD) and below (cooling, CDD) a standard level (65° F or 18 °C) are traded, since it is considered that the further the temperature moves away from this standard level, the greater the energy consumption (higher costs) for cooling and heating, respectively. In addition, to avoid the different influence played by the human factor on the data, the temperature taken as underlying is the one obtained from the airports of each city, since data collection is considered to be standardized and is more independent of the human factor (among others) than other weather stations. Finally, the daily temperature used is the average between the maximum and minimum observed.

From the above, we define $Temp_t$ as the change of relative temperature degrees of day t with respect to the standard temperature (18 °C), that is:

$$Temp_t = [\frac{\frac{max_t+min_t}{2}}{18} - 1] - [\frac{\frac{max_{t-1}+min_{t-1}}{2}}{18} - 1] = \frac{\frac{max_t+min_t}{2} - \frac{max_{t-1}+min_{t-1}}{2}}{18} \tag{1}$$

where max_t and min_t are the maximum and minimum temperatures for each day, respectively.

2.2. Temperature shocks identification

To determine the temperature shocks, unlike the literature reviewed above, we use an outlier identification methodology. Then, to extract the extreme data from above relative temperature (see expression-(1)), we use the GUB (Good-Usual-Bad) decomposition developed by González-Sánchez (2021). This technique of decomposition of a time series allows separating the observations into three statistically independent groups which makes their subsequent analysis easier; these groups are composed of the positive outliers (Good), the negative outliers (Bad) and the central part that behaves as a normal distribution. By applying this technique, we can then extract those data of high extreme temperature (Good, in our case $Heating$) and low extreme temperature (Bad, for our study $Cooling$). Note that this is the first time this methodology is applied to temperature and, unlike the rest of the studies referenced above, it does not consider extreme temperature as a certain and subjective percentile or the residual of a mean temperature fit model, with greater or lesser goodness of fit; on the contrary, our data are extreme if they show non-Gaussian behavior.

The GUB decomposition is an iterative procedure which first assumes that we select τ_n, τ_n, τ_a, $\tau_{a,2}$ and τ_h as the test of normality, autocorrelation, autocorrelation for the square of data and heteroskedasticity, respectively. Then, we identify outliers as follows:

1. For $t = 1$ to T, we search $max|Temp_t|$.
2. According to the sign of this data, we include it in a positive ($Heating$) or negative ($Cooling$) outlier series and in the usual ($Usual$) time series we replace the original return value with zero. Note that this procedure makes all three series independent (for more details see González-Sánchez (2021)).
3. After replacement, we re-estimate τ_n, τ_n, τ_a, $\tau_{a,2}$ and τ_h in this new usual time series and if the hypotheses on normality, non-autocorrelation and non-heteroskedasticity are accepted then the procedure stops; otherwise, we go back to step (1) and repeat the procedure until the usual time series passes the tests.

2.3. Asset return sensitivity of temperature

Next, we calculate at the end of each month the sensitivity of the daily return of the previous year to each temperature series obtained. Thus, if $r_{i,t}$ is the excess daily return of asset i over the risk-free rate, while $Heating_t$, $Usual_t$ and $Cooling_t$ are the values of the previous relative temperature decomposition Good, Usual and Bad, respectively, then the sensitivities to temperature shocks (hot and cold) at date m (month and year) of asset i are defined as:

$$\begin{aligned} \delta^H_{i,t} &= \frac{cov(r_{i,t}, Heating_t)}{var(Heating_t)} \\ \delta^U_{i,t} &= \frac{cov(r_{i,t}, Usual_t)}{var(Usual_t)} \\ \delta^C_{i,t} &= \frac{cov(r_{i,t}, Cooling_t)}{var(Cooling_t)} \end{aligned} \tag{2}$$

where δ^H and δ^C show the sensitivity of daily asset returns to daily hot and cold temperature shocks, respectively and, δ^U shows the sensitivity of daily asset returns to usual temperature. Note that these sensitivities are calculated with respect to the temperature recorded at the corresponding airport.

2.4. Estimation of the temperature factor in asset pricing

Then, and unlike Balvers et al. (2017), we estimate the return of the temperature factor along the same lines as the other usual factors in asset pricing. In other words, the asset pricing factors most commonly used in the financial literature are as follows:

- From Fama and French (1993): market factor or excess return on risk-free rate of market portfolio ($Mkt - Rf$); this factor shows the systematic risk of CAPM. Also Fama and French (1993) defined: size factor or small minus big firms' market returns, where size is measured by book-to-market ratio (SMB) and earnings–price ratio or high minus low firms' market returns, using earnings-price and book-to-market ratios to classify the firms (HML).
- From Carhart (1997): persistence of returns or momentum (WML) defined as the difference of the portfolio returns formed by high return assets (lags) minus the portfolio returns of assets with low returns.
- From Fama and French (2015): difference between the returns on diversified portfolios of stocks with robust and weak profitability (RMW) and the difference between the returns on diversified portfolios of the stocks of low (conservative) and high investment (aggressive) firms (CMA).

Note that factors are defined as difference between the returns of the positive sensitive assets (or higher positive effect) to each financial factor and the returns of the negative sensitive assets (or higher negative effect). Then, we define three factors of temperature effect, Hot $Normal$ and $Cold$, which collect the difference between the returns of the positive sensitive (one percentile of the corresponding δ distribution calculated from expression-(2)) and negative sensitive (1 minus the chosen percentile of the δ distribution) assets to the Hot, $Usual$ and $Cold$ temperatures, respectively.

Thus, if J_H the number of assets least sensitive to $Heating$, J_C the number of assets least sensitive to $Cooling$, S_H the number of assets most sensitive to $Heating$ and S_C the number of assets most sensitive to $Cooling$, then J_N and S_N are the number of assets least and most sensitivity to normal temperature, respectively; whereby the factor returns are:

$$\begin{aligned} Hot_t &= \frac{1}{J_H}\sum_{j=1}^{J_H} r_{j,t} - \frac{1}{S_H}\sum_{s=1}^{S_H} r_{s,t} \\ Cold_t &= \frac{1}{J_C}\sum_{j=1}^{J_C} r_{j,t} - \frac{1}{S_C}\sum_{s=1}^{S_C} r_{s,t} \\ Normal_t &= \frac{1}{J_N}\sum_{j=1}^{J_N} r_{j,t} - \frac{1}{S_N}\sum_{s=1}^{S_N} r_{s,t} \end{aligned} \tag{3}$$

Note that while the Hot and $Cold$ factors are calculated from the returns positive and negative sensitivity to these extreme temperatures (according to the selected percentile), the $Normal$ factor is similarly estimated from asset returns that do not show extreme sensitivity to temperature, but they show positive and negative sensitivity to usual temperatures. In addition, while temperature sensitivities are calculated at the local (country) level, the factor is estimated globally for the entire geographical area studied.

2.5. Calculating betas

The following, we calculate the sensitivity of each asset return to each of the factors commonly used in asset pricing and, in addition, to the previously estimated temperature factors. Thus, at the end of each month the sensitivity of the previous year's daily return to any one of the factors (f) is:

$$\beta_{i,m}^{f} = \frac{cov(r_{i,t}, f_t)}{var(f_t)} \tag{4}$$

where f are $Mkt - Rf$ (market portfolio), SMB (size or value factor), HML (growth factor), WML (momentum factor), RMW (profitability factor) and CMA (conservative factor); and also, our three temperature factors Hot (heat shocks or extreme heat temperature factor), $Cold$ (cold shocks or extreme cold temperature factor) and $Normal$ (usual temperature factor). In this way, we can distinguish the effects of temperature shocks from those caused by the usual temperature.

2.6. Risk premium estimation

Finally, following Fama and MacBeth (1973), as usual in the literature, we determine the monthly (m) risk premia (λ) for each factor f of the total of F factors, from the previous estimation of the following cross-section expression. So,

$$r_{i,m} = \lambda_0 + \sum_{f=1}^{F} \lambda_f \cdot \beta_{i,m}^{f} \tag{5}$$

Thus, if we include the six usual financial factors and compare the results with the temperature factors, we analyze the explanatory power of one versus the other. Note also that the inclusion of all these financial factors, unlike the literature reviewed, gives robustness to our results, since if the temperature factors were not significant when included together with the financial factors, it would indicate that the information from the temperature factors is already included in the rest of the financial factors.

Table 1
Average values of relative changes of temperature.

Country	$Heating$	$Usual$	$Cooling$	% days heating	% days usual	% days cooling
Austria	0.3077	0.0035	−0.3359	2.76%	93.75%	3.49%
Belgium	0.2927	0.0000	−0.3140	2.98%	94.26%	2.77%
Denmark	0.3077	−0.0014	−0.3017	2.77%	94.84%	2.38%
Finland	0.4577	−0.0013	−0.4201	2.27%	95.55%	2.18%
France	0.3027	0.0006	−0.3273	2.03%	95.92%	2.05%
Germany	0.3194	0.0016	−0.3278	2.68%	94.25%	3.07%
Ireland	0.2351	−0.0023	−0.2333	4.40%	92.06%	3.54%
Italy	0.2598	0.0020	−0.2711	1.89%	95.61%	2.50%
Netherlands	0.2961	−0.0004	−0.3044	2.41%	95.38%	2.21%
Norway	0.3788	−0.0025	−0.3604	2.63%	95.26%	2.11%
Portugal	0.2458	−0.0003	−0.2441	2.42%	95.25%	2.33%
Spain	0.2926	0.0029	−0.3103	1.89%	95.44%	2.68%
Sweden	0.3404	−0.0005	−0.3253	2.26%	95.51%	2.23%
Switzerland	0.2954	0.0036	−0.3250	2.38%	94.42%	3.20%
UK	0.3003	−0.0002	−0.3021	2.80%	94.48%	2.72%
Average	0.3088	0.0004	−0.3135	2.57%	94.80%	2.63%

Note: This table shows the average relative daily changes (in terms of the standard temperature of 18 °C) for each country resulting from the GUB decomposition, thus heating shows the relative daily non-Gaussian and hot changes; usual shows the daily Gaussian changes; cooling represents the daily non-Gaussian and cold changes. In addition, % days shows the percentage of days out of the total sample where extreme hot ($Heat$), cold ($Cooling$) or Gaussian ($Usual$) changes occur.

3. Data

Our sample consists of the daily prices of European company stocks from January 1, 2002 to March 31, 2023. In order to have a representative sample we have selected all companies that are part of the most relevant European[2] stock indexes: Austria (ATX, 20 firms), Belgium (BEL, 20 firms), Denmark (OMXC, 25 firms), Finland (OMX Helsinki, 25 firms), France (CAC, 40 firms), Germany (DAX, 40 firms), Ireland (ISEQ, 20 firms), Italy (MIB, 40 firms), Netherlands (AEX, 25 firms), Norway (OMX Oslo, 20 firms), Portugal (PSI, 20 firms), Spain (IBEX, 35 firms), Sweden (OMXS, 30 firms), Switzerland (SMI, 20 firms), United Kingdom (FSTE, 100 firms). Data (daily prices of 480 companies) are obtained from Bureau van Dijk's OSIRIS database in US dollars as Fama–French factors.

For the same time period, we free-download from French's data web[3] the European financial factors daily data and the risk-free rate (Rf) to calculate the excess of daily return over the risk-free rate of each asset.

Daily temperature data corresponding to the city and country of each stock index that we free-download from the European Climate Assessment & Dataset.[4] Of the more than 25,000 weather stations for which data is available, we selected those corresponding to the city airport as Dupuis (2011), since the data guarantee: homogeneity in data collection, sufficient historical data base without gaps and missing data, they correspond to representative centers of economic activity and the human effect is similar among them. Moreover, we cannot forget that if an economic agent decided to hedge temperature risk, weather derivatives use the temperature of airports and also, in our study, the temperature variable (see expression-(1)) has been defined following the standards of the temperature derivatives market.

4. Results

First, we estimated the daily relative changes of each country's temperature (expression-(1)). Next, we performed the GUB decomposition of these temperatures for each country. The results are in Table 1.

The usual sign shows the most common direction of daily temperature changes, e.g., in Norway (−0.0025) there are usually daily temperature decreases, while in Spain (0.0029) daily temperature increases are more common. The means of the relative daily temperature changes indicate that the extreme heat temperature days are more than 5 °C (0.3088 · 18 °C), the extreme cool days have a mean value of less than −5 °C (−0.3135 · 18 °C) and the usual mean changes are approximately 0.006 °C (0.0004 · 18 °C). As for the extreme observations, we find that heating days (2.57%) are slightly less than cooling days (2.63%), while the usual temperature is present in 94.80% of the cases. However, when we analyze the data by country, we find different evidence that corroborates the evidence found in previous work and requires the inclusion of the effect of the geographical area in the modeling, i.e., the effect of temperature cannot be replaced by a single index but must be studied according to the geographical location of the market. As a consequence of this evidence, we calculated the sensitivity of the returns of each company to the relative variation of the temperature of the country to which the market where the stock is traded belongs, and then we apply expression-(2) to calculate the sensitivity of each stock return to extreme heat ($Heating$), extreme cold ($Cooling$) and the usual temperature ($Usual$) of market country where the corresponding stock is traded. Table 2 shows the results.

2 We have selected developed European countries as cataloged by French's website, as the risk factors are constructed from the stocks of these countries.
3 mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.htm.
4 ecad.eu/dailydata/predefinedseries.php.

Table 2
Average values of stock return sensibility to relative changes of temperature.

Country	$mean_{heating}$	$max_{heating}$	$min_{heating}$	$mean_{usual}$	max_{usual}	min_{usual}	$mean_{cooling}$	$max_cooling$	$min_{cooling}$
Austria	0.0445%	2.1671%	−1.6769%	0.1258%	2.6981%	−4.0415%	0.0371%	2.5351%	−2.2949%
Belgium	0.0320%	2.7209%	−1.7620%	0.1435%	8.4719%	−3.1094%	−0.0373%	3.3850%	−2.4711%
Denmark	0.0431%	1.7759%	−2.7636%	−0.1473%	3.8831%	−6.9363%	−0.1180%	1.8784%	−3.1244%
Finland	0.0166%	1.8941%	−2.0091%	0.0171%	6.0990%	−4.5014%	−0.0642%	1.7144%	−3.6727%
France	0.0128%	3.4893%	−2.1444%	0.0836%	5.7525%	−5.6630%	−0.0584%	3.7981%	−5.0277%
Germany	0.0448%	2.9220%	−3.7720%	−0.1111%	5.0309%	−9.7182%	0.0284%	3.8413%	−4.1447%
Ireland	0.0641%	3.0363%	−2.5477%	0.2289%	5.2128%	−4.8539%	−0.0804%	3.2364%	−2.1293%
Italy	−0.0188%	3.6900%	−3.2255%	0.0925%	5.0970%	−5.6850%	0.1150%	3.2394%	−2.5632%
Netherlands	0.0233%	3.4925%	−2.3765%	0.1847%	7.7235%	−3.3281%	0.0237%	5.6394%	−3.0493%
Norway	0.1717%	4.1167%	−4.1014%	−3.0941%	5.3413%	−10.3772%	−0.0168%	2.5125%	−3.6428%
Portugal	0.0150%	2.8623%	−2.8374%	−0.1545%	5.3955%	−9.4023%	−0.0182%	2.6307%	−4.9986%
Spain	−0.0314%	1.5452%	−3.0411%	−0.2496%	4.5722%	−4.2687%	−0.0304%	3.5232%	−6.0936%
Sweden	−0.0336%	2.0987%	−4.8800%	−0.2297%	5.2777%	−5.8429%	−0.0157%	2.3437%	−2.2160%
Switzerland	−0.0004%	1.4991%	−2.3060%	−0.1949%	3.6839%	−6.4336%	−0.0016%	2.7854%	−2.5078%
UK	0.0116%	5.3668%	−8.2700%	0.2995%	4.1002%	−4.0406%	0.0348%	2.9664%	−2.5380%
Average	0.0264%	2.8451%	−3.1809%	−0.2004%	5.2226%	−5.8801%	−0.0135%	3.0686%	−3.3649%

Note: This table shows the average sensitivity of the stock returns of companies in each country to extreme hot ($Heat$) and extreme cold ($Cooling$), as well as the highest positive and negative sensitivities (max. and min., respectively).

Table 3
Most frequent firms in each extreme temperature factor.

Component temperature and effect sign	Name	Country	% times	Average sensitivity
Hot positive effect	Petroleum Geo Services	Norway	34.43%	0.07%
Hot negative effect	Subsea7 (North Sea engineering)	Norway	18.85%	−0.10%
Normal positive effect	Taylor Wimpey PLC (building)	UK	23.77%	0.52%
Normal negative effect	Petroleum Geo Services	Norway	34.84%	−3.03%
Cold positive effect	Mediobanca (bank)	Italy	22.95%	0.30%
Cold negative effect	Navigator (paper manufacturing)	Portugal	21.31%	−0.02%

Note: This table shows the company that has most frequently been part of each component (positive or negative sensitivity) of the temperature risk factors (Hot and $Cold$).

The results show that the sensitivity of stock returns to extreme temperatures (heating and cooling) depends on geographic location, as we had already shown, but we observe that the effect is asymmetric, i.e., the effect of heating is not like that of cooling in each geographic location. This new evidence reinforces our proposal to treat extreme hot and cold temperatures separately, an issue that has not been studied in the financial literature yet. Another relevant issue is that the average effect of cooling is higher than that of heating; the effect is negative, in line with the evidence found in the literature regarding the negative relationship between temperature and asset performance. However, if we analyze it by country, we find that this does not occur in all cases, for example, the heating effect is greater than the cooling effect in Italy, so that the average sensitivity of Italian companies to heating is negative, while for extreme cooling it is positive. In addition to the geographical location, the effect of temperature is different in companies depending on the economic activity of each firm.

Now, following Fama and French (1993) we apply expression-(3) to estimate the Hot, $Cold$ and $Normal$ temperature factors. Thus, the Hot, $Cold$ and $Normal$ factor returns are estimated as the difference between the equal-weighted sum of the daily return of the companies in the sample with lower and higher sensitivity to extreme hot ($Heating$) and cold ($Cooling$) temperatures and the usual temperatures ($Usual$) in each month. We consider the 5% and 95% percentile as extreme values of lower and higher sensitivity. Then, Hot and $Cold$ factors are defined as the return on assets with lower temperature effects versus those with higher effects, in line with, for example, the size factor or SMB, which represents the returns of small versus big companies. As an example, Table 3 shows the companies that have most frequently been part of each factor, either as the worst affected or as the most benefited by each temperature component.

For example, we find that two Norwegian companies are the most frequent within the Hot factor, despite the fact that, as a consequence of Norway's geographical location, its temperatures are colder than in other countries further south in Europe. Thus, the results reveal that business activity and geographical location do not always have to influence the sensitivity of stock return to temperature components in the same direction.

Table 4 shows the average frequency of participation in each factor (Hot, $Normal$ and $Cold$) of the firms from each country differentiated by sign of the effect.

The results show that when the temperature (heat component) is extreme the most affected companies are Norwegian (positively, 15.87%) and Italian (negatively, 13%); therefore, there is a clear geographical effect as companies further north in Europe show a favorable effect against extreme heat while the effect on companies further south is negative. It is not, however, the only one. Swedish companies, for instance, have more negative effects (frequency of 8.49%) than positive (frequency of 4.66%).

We also observe that the geographical effect is the opposite when the factor studied is cold, since Italian companies are the most frequent to display a positive effect (16.32%) and companies from the United Kingdom are the most frequent (12.70%) to display

Table 4
Average participation of firms by country in each temperature factor.

Country	$Hot(+)$	$Hot(-)$	$Normal(+)$	$Normal(-)$	$Cold(+)$	$Cold(-)$
Austria	3.39%	3.20%	3.65%	1.97%	6.33%	5.25%
Belgium	1.94%	3.06%	1.86%	1.42%	1.15%	2.35%
Denmark	4.69%	4.88%	3.69%	6.04%	2.50%	5.59%
Finland	8.42%	6.18%	5.66%	4.10%	3.09%	5.14%
France	4.62%	7.19%	14.49%	7.15%	8.12%	9.91%
Germany	8.05%	6.11%	4.36%	7.00%	8.46%	6.04%
Ireland	5.18%	3.50%	2.57%	1.53%	2.24%	5.37%
Italy	12.30%	13.00%	13.79%	10.02%	16.32%	9.91%
Netherlands	2.68%	4.02%	4.10%	2.01%	4.66%	3.43%
Norway	15.87%	6.82%	7.79%	17.32%	7.86%	6.93%
Portugal	8.42%	8.79%	7.41%	8.01%	6.48%	8.12%
Spain	4.88%	9.09%	4.92%	9.76%	9.35%	12.30%
Sweden	4.66%	8.49%	3.39%	12.97%	4.96%	2.94%
Switzerland	0.89%	2.20%	1.68%	5.03%	3.20%	4.02%
UK	14.01%	13.45%	20.64%	5.66%	15.28%	12.70%

Note: This table shows the average participation of each country's companies' return in each temperature factor return (Hot, $Normal$ and $Cold$) and according to the sign of the sensitivity of each company's stock performance to the country's temperature component ($Heat$, $Usual$ and $Cooling$).

Table 5
Hot, $Normal$ and $Cold$ temperatures betas.

Country	mean Hot	max. Hot	min. Hot	mean $Normal$	max. $Normal$	min. $Normal$	mean $Cold$	max. $Cold$	min. $Cold$
Austria	−0.0983	2.7073	−2.1968	0.0455	1.8454	−1.6495	0.1578	4.1667	−1.6076
Belgium	−0.0287	1.8982	−1.8670	0.0908	1.9081	−1.8714	0.1601	2.5112	−2.5149
Denmark	−0.0822	2.3406	−3.2721	0.1021	3.1755	−1.8232	0.2781	3.8136	−2.4650
Finland	0.2690	9.4183	−4.3695	−0.6581	5.6297	−9.8176	0.6150	5.3536	−8.7542
France	−0.0557	1.8534	−2.7865	−0.0548	1.5328	−4.9617	−0.0222	2.0914	−4.3292
Germany	−0.0589	1.9838	−3.3733	0.0863	3.5151	−0.8641	0.1329	2.8356	−1.1328
Ireland	−0.0152	9.3239	−2.2383	0.0364	2.0443	−8.7539	0.0380	3.9741	−7.9866
Italy	−0.0821	7.0230	−4.0001	0.0928	6.8630	−1.8290	0.2197	4.1667	−2.5003
Netherlands	−0.0605	2.0112	−2.5005	0.0676	3.2295	−1.9045	0.1721	4.0873	−1.3625
Norway	0.0167	2.5123	−1.3883	0.1234	1.7298	−1.9977	0.0601	1.9540	−1.6674
Portugal	−0.0579	1.5921	−1.5978	0.0297	1.3282	−2.2932	0.1741	2.0193	−1.5837
Spain	−0.0660	1.3683	−1.9281	0.0234	1.5323	−3.4774	0.0346	2.5263	−1.4255
Sweden	−0.0939	1.7204	−2.3183	−0.0642	2.2976	−9.1050	0.1283	2.2938	−1.7754
Switzerland	−0.1090	2.2871	−4.5708	0.0552	2.4485	−2.2959	0.3099	4.3588	−3.5201
UK	0.0037	3.5687	−4.3392	0.1348	3.8295	−3.0096	0.2489	4.5078	−2.4021
Average	−0.0346	3.4406	−2.8498	0.0074	2.8606	−3.7102	0.1805	3.3773	−3.0018

Note: This table shows the sensitivity (measured by the beta) of asset returns to the returns of the factors representing temperature ($Heat$, $Usual$ and $Cooling$), thus mean Hot ($Normal$ and $Cold$) by country shows the average betas of the companies of each country against the factor of $Heat$ ($Usual$ and $Cooling$); max. Hot ($Normal$ and $Cold$) is the highest beta calculated for the companies of each country against the factor of $Heat$ ($Usual$ and $Cooling$); min. Hot ($Normal$ and $Cold$) is the lowest beta of the companies of a country against the factor of $Heat$ ($Usual$ and $Cooling$).

a negative effect. Again, the geographical effect is not the only relevant one. Spanish companies (located in southern Europe), for example, show a higher frequency of negative effect (12.30%) than positive (9.35%) for the cold factor.

The above evidence is also repeated in the normal temperature factor, since Swedish companies are the most frequent to display a negative effect (12.97%) while Italian companies more frequently show a positive effect (13.79%). We can deduce that latitude is a fundamental effect, but in the Spanish case, for example, note that this effect is not the most relevant, since the presence of Spanish companies with a positive effect (4.92%) is less than those with a negative effect (9.76%) to the usual changes in temperature.

Table 5 shows a summary of the betas calculated monthly with daily data during the previous year of asset returns against each of the risk factors by temperature.

Note that the $Cold$ betas are higher than the Hot betas, while the betas to the $Usual$ temperature changes ($Normal$ factor) are very small. The most extreme $Cold$, Hot and $Normal$ betas occur in Finnish companies, Finland being the northernmost country in the sample. Finally, we observe that the betas associated with the temperature factors show high variability.

Table 6 presents the correlation matrix among the pricing factors used in this empirical study.

Note that the factors representing temperature show very low correlations with the other factors, the highest being Hot with WML or Momentum (−0.1042), in any case much lower than other correlations between the commonly used factors. Therefore, the information contained in the Hot, $Normal$ and $Cold$ factors does not seem to be already included in other pricing factors.

Finally, Table 7 shows the risk premiums estimated following Fama and MacBeth (1973).

First, note that when including temperature factors, the $adjusted\ R^2$ increases. $CAPM$, for example, has a goodness of fit of the model of 4.50%, while for $CAPM + Temperature$ model is 11.40%. Similarly, root-mean-square error or $RMSE$ decreases. Therefore, given that the correlation of the temperature factors and the rest of the valuation factors was very low, we can conclude that temperature changes are an explanatory factor for asset pricing. This evidence is also confirmed by observing how the $Constant$

Table 6
Factors correlation matrix.

	Mkt-Rf	SMB	HML	RMW	CMA	WML	HOT	NORMAL	COLD
Mkt-Rf	1								
SMB	−0.6201	1							
HML	0.2430	−0.1257	1						
RMW	−0.1842	0.1847	−0.6116	1					
CMA	−0.2155	0.0400	0.4108	−0.3534	1				
WML	−0.3789	0.3607	−0.2979	0.3052	0.0702	1			
HOT	0.0831	−0.0863	−0.0381	−0.0810	−0.0391	−0.1042	1		
NORMAL	−0.0236	0.0274	−0.0139	0.0344	0.0093	0.0234	−0.0092	1	
COLD	−0.0018	0.0553	0.0549	−0.0096	−0.0302	−0.0272	−0.0495	0.0074	1

Note: This lower triangular matrix shows the Spearman correlation coefficients for each pair of risk factors, including factors associated with temperature changes.

Table 7
Risk premium results.

Factor	Estimation	$CAPM$	FF	$CAPM + Temperature$	$FF + Temperature$	$Best\ model$
Constant	param.	0.0066	0.0054	0.0052	0.0048	0.0052
	tvalue	11.61**	10.17**	9.93**	4.51**	7.43**
Mkt-Rf	*param.*	−0.0051	0.0105	−0.0031	0.0103	0.0174
	tvalue	−5.61**	5.22**	−3.13**	3.47**	5.56**
SMB	*param.*		0.0059		0.0061	0.0071
	tvalue		8.19**		7.54**	8.97**
HML	*param.*		−0.0076		−0.0072	−0.0054
	tvalue		−7.90**		−4.58**	−5.31**
RMW	*param.*		−0.0003		−0.0004	
	tvalue		−0.74		−0.76	
CMA	*param.*		0.0020		0.0016	0.0013
	tvalue		4.58**		2.07*	2.98**
WML	*param.*		−0.0013		−0.0015	
	tvalue		−0.99		−1.20	
HOT	*param.*			0.0162	0.0082	0.0074
	tvalue			3.15**	2.17*	2.14*
NORMAL	*param.*			0.0123	0.0036	
	tvalue			1.98*	0.47	
COLD	*param.*			0.0178	0.0119	0.0110
	tvalue			2.59**	2.26**	2.35**
$Adjusted\ R^2$		4.50%	15.03%	11.40%	18.03%	14.98%
$RMSE$		7.32%	6.78%	6.98%	6.07%	6.80%

Note: $CAPM$ is the Capital Asset Pricing Model; FF is the 6-factor model from Fama and French (2015); $Bestmodel$ is model that only includes statistically significant factors; *param.* is the parameter estimated by least squares according to the Fama and MacBeth (1973) methodology; *tvalue* is the statistical significance of the parameter estimated from standard errors robust to autocorrelation and heteroscedasticity (Newey–West with 12 lags as the returns are monthly); $Adjusted\ R^2$ is the goodness-of-fit level of each model corrected for degrees of freedom; $RMSE$ is the root-mean-square error.

** Mean that it is significant at a 1% confidence level.

* Mean that it is significant at a 5% confidence level.

of the models, when incorporating the temperature factors, decreases its value with respect to the traditional financial models, although it is still statistically significant.

Regarding the explanatory factors, we observe that RMW and WML are not significant in the case of the European companies in the sample. We also found that the $Normal$ temperature factor is significant at a 5% confidence level when we only include the market portfolio ($Mkt - Rf$) as a financial factor, but when we include the rest of the financial factors, it is no longer significant. Therefore, the temperature factors with explanatory capacity for assets pricing are the extreme changes in temperature, both Hot and $Cold$. This is relevant and shows the robustness of our results to previous studies, as we find empirical evidence that a portfolio composed of assets that do not show high-low sensitivity to extreme temperature changes does not provide new information with respect to the usual financial factors.

Within the financial factors, the market portfolio ($Mkt - Rf$) is the highest monthly risk premium (1.74%), while the size factor or SMB is the second highest monthly risk premium (0.71%), followed by the growth factor or HML (−0.54%) and finally the conservatism and aggressiveness of investment factor or CMA (0.13%). But if we compare these results with the extreme temperature risk premiums, we find that the risk premium for extreme cold temperatures or $COLD$ is 1.1%, only surpassed by the market portfolio. Similarly, the risk premium for extreme hot temperatures or HOT is 0.74%, higher even than the size factor premium.

Table 8
Average asset return by percentile sensitivity to temperature factor.

Factor	5%	25%	50%	75%	95%
Hot	0.66%	0.40%	0.28%	−0.24%	−0.34%
$Normal$	−0.32%	0.16%	0.81%	−0.30%	0.19%
$Cold$	0.63%	0.41%	0.21%	−0.14%	−0.27%

Note: Percentiles range from least (5%) to most sensitive (95%) to temperature factors.

In short, the extreme changes in temperature (hot and cold) show an explanatory capacity in the cross-section models of asset pricing that is higher than the usual financial factors. So, if we compare the six-factor model (FF) with the model that only includes the statistically significant factors ($Bestmodel$), with six factors as well, we observe that while the FF model presents an $adjusted R^2$ and $RSME$ of 15.01% and 6.78%, respectively, the $Best\ model$ obtains better results ($adjusted R^2$ of 15.11% and $RSME$ of 6.62%) and all explanatory variables are statistically significant and show lower cross-correlations.

Finally, in order to contrast the robustness of our results, Table 8 shows the mean return of the following month ($m + 1$) of that asset whose sensitivity to the corresponding temperature factor occupies in each month (m) the respective percentile.

Note that while the mean return for the extreme temperature factors (hot and cold) grows with the percentile of the sensitivities distribution and goes from high positive sensitivity to high negative sensitivity, as expected according to evidence found in the literature, the same is not true for the normal temperature factor. Thus, the empirical results on the statistical significance of the risk premiums for the extreme temperature factors (hot and cold) seem to be justified; similarly, the erratic behavior of asset returns against the normal temperature factor would justify the non-statistical significance of the corresponding premium, and according to the results of Table ??, it seems rather that this factor is already included in the usual financial factors.

5. Conclusions

The financial literature has studied the effects of weather on asset returns through weather-induced changes in investor mood, therefore, it is a behavioral finance approach. In contrast, studies on the effect of weather on asset pricing, using factor models and estimating the corresponding weather risk premia, are scarcer (Balvers et al., 2017), for example, is an exception. Thus, in the financial literature there is a gap in the analysis of climate risk premiums in asset pricing, but applying methodology consistent with that used to estimate the risk financial factors.

From the literature reviewed above, we found that extreme climate changes do not have the same effects as expected changes, and furthermore, such changes are conditioned by the latitude of the countries, among other elements.

Our proposed innovative methodology is developed as follows: first, we apply a GUB decomposition (González-Sánchez, 2021) to extract the extreme $Heat$, $Cooling$ and $Usual$ (Gaussian) temperature changes for each country in the sample; next, we calculate the sensitivity of each country's asset return to extreme and usual temperature changes. From these sensitivities, we construct asset pricing factors for the $Heat$, $Cooling$ and $Usual$ temperature changes in the whole sample, as the difference between the 5% equal-weighted returns with higher positive and higher negative sensitivities; finally, we calculate the betas of all assets to these factors and estimate cross-section risk premia for the usual financial factors and the three temperature factors (Hot, $Normal$ and $Cold$).

Our study sample is made up of the daily prices of the companies that are part of the stock market indexes of the 15 most developed European countries using the airport temperature of the capital of each country as the country temperature.

The results show that the estimated temperature factors are poorly correlated with the rest of the financial factors. Despite that, we find evidence that only the extreme changes in temperature (hot and cold) have explanatory power for asset returns and that this power is greater than the rest of the financial factors used, except for the market portfolio. As a consequence, only extreme temperature changes are a factor to be considered in asset pricing.

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CRediT authorship contribution statement

Mariano González-Sánchez: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Raquel Arguedas Sanz:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Ana I. Segovia San Juan:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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