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Stock market returns: A note on temperature anomaly

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Abstract

This study investigates whether stock market returns are related to temperature. Research in psychology has shown that temperature significantly affects mood, and mood changes in turn cause behavioral changes. Evidence suggests that lower temperature can lead to aggression, while higher temperature can lead to both apathy and aggression. Aggression could result in more risk-taking while apathy could impede risk-taking. We therefore expect lower temperature to be related to higher stock returns and higher temperature to be related to higher or lower stock returns, depending on the trade-off between the two competing effects. We examine many stock markets world-wide and find a statistically significant, negative correlation between temperature and returns across the whole range of temperature. Apathy dominates aggression when temperature is high. The observed negative correlation is robust to alternative tests and retains its statistical significance after controlling for various known anomalies.

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1. Introduction

As behavioral finance takes its roots in mainstream financial research, a sub-field has emerged which studies the impact of weather conditions on investors' behavior, and subsequently, the stock market returns. If weather conditions can affect mood or cause mood misattribution, then they can influence investors' risk aversion and risk assessments, which in turn affect their investment behavior. This study investigates whether temperature influences stock market returns.

It has long been recognized that mood, feelings and emotions play an important role in making decisions and forming judgments. For instance, Schwarz (1990), and Loewenstein et al. (2001) provided theories linking mood and feelings to general decision-making, while Etzioni (1988); Romer (2000); Hanock (2002), and Mehra and Sah (2002) established the importance of emotions in economic decision-making. Mood itself can be influenced by situational and environmental factors (Watson, 2000), some of which may cause mood misattributions (Schwarz and Clore, 1983; Schwarz, 1990; Clore and Parrot, 1991). For instance, people tend to rate their life satisfactions much higher on sunny days than on cloudy or raining days (Schwarz and Clore, 1983), although their well-being does not change on a daily basis. In fact, there is a large body of literature on the links between weather variables and human behavior (e.g., Wyndham, 1969; Bell and Baron, 1976; Moos, 1976; Allen and Fisher, 1978; Cunningham, 1979; Schneider et al., 1980; Bell, 1981; Sanders and Brizzolara, 1982; Howarth and Hoffman, 1984; Rind, 1996; Watson, 2000; Parsons, 2001; Pilcher et al., 2002).

In a comprehensive study encompassing many weather variables, Howarth and Hoffman (1984) found that humidity, temperature and amount of sunshine exert the greatest influence on mood. In particular, they found that these three climatic conditions had significant effects on concentration and, under cold temperature, say between $-8\,°C$ and $-28\,°C$, subjects reported increased aggressive feelings. [1] Other studies have examined the impact of ambient temperature alone on mood, behavior and task performance. Allen and Fisher (1978), and Wyndham (1969) both found that task-performing abilities are impaired when individuals are exposed to very high or low temperature. This finding was later confirmed in a meta-analytic review by Pilcher et al. (2002). Wyndham (1969) found behavioral changes in the form of hysteria and apathy under extreme heat. Meantime, Cunningham (1979), and Schneider et al. (1980) concluded that people tend to be less willing to extend help to others when subject to hot or cold temperature. On the predisposition of aggression, researchers (e.g., Baron and Ransberger, 1978; Palamerek and Rule, 1980; Bell, 1981; Howarth and Hoffman, 1984) have gathered evidence that suggests increased level of aggression at high ambient temperature. By the same token, Schneider et al.

[1] The subject pool of this study consisted of 24 university students who were monitored over an 11-day period. Watson (2000) conducted a study involving a total of 478 students over a longer time period. He found no significant link between mood and weather variables, including the level of sunshine, precipitation, barometric pressure, and temperature. However, he only reported the testing results related to sunshine and precipitation.

(1980) concluded that cold temperature can also lead to aggression. On the whole, it appears that very high or very low temperatures tend to cause aggression; and that high temperature can also cause hysteria and apathy.

Saunders (1993) was the first to link investment behavior to weather conditions. Focusing on the City of New York for the period of 1927–1989, he showed that less cloud cover is associated with higher returns, and the return difference between the most cloudy days and the least cloudy days is statistically significant. The results confirm the conjecture that investors' mood is upbeat or optimistic on sunny days, which uplifts the stock market returns, and that their pessimistic mood on cloudy days depresses the stock returns. These findings were confirmed by Hirshleifer and Shumway (2003) who examined 26 stock market indices around the globe for the period of 1982–1997.

Kamstra et al. (2003) examined the impact of seasonal affective disorder (SAD) on stock market returns. Based on psychological and clinical evidence that longer nights cause depression, the authors conjectured that longer nights should be associated with lower stock returns due to the SAD effect or ''winter blues''. This hypothesized relationship was confirmed for many international markets. [2]

The current paper examines the potential linkage between temperature and stock returns. As stated earlier, the psychological literature suggests that temperature is one of the three important weather variables affecting people's mood. Just as the amount of sunshine or the length of the night affect investors' behavior by altering their mood, we expect a similar linkage between temperature and market returns. Given the psychological evidence reviewed above, we hypothesize that lower temperature is associated with higher stock market returns due to aggressive risk taking, and higher temperature can lead to either higher or lower stock returns since both aggression (associated with risk-taking) and apathy (associated with risk-averting) are possible behavioral consequences and the net impact on investors' risk taking depends on the trade-off between the two.

We find that stock returns are negatively correlated with temperature: the lower the temperature, the higher the returns, and vice versa. The relationship is slightly weaker in the summer than in the winter, implying that when temperature is high, apathy dominates aggression, resulting in lower returns. Nevertheless, a statistically significant, overall negative correlation exists between temperature and stock returns. This correlation is prevalent among stock markets around the globe, and robust to various alternative tests and specifications. It remains strong even after controlling for the geographical dispersion of investors relative to the city where the stock exchange resides.

[2] In a separate study, Kamstra et al. (2000) found that returns are substantially lower on the weekends coinciding with the daylight-savings time changes. They postulated that the disruption of sleep patterns around the time change would impair judgment and raise anxiety, which in turn causes investors to seek for safety and avoid risk-taking. Finally, two groups of authors (Dichev and Janes, 2001; Yuan et al., 2001) independently documented a relationship between lunar phases and stock market returns. They showed that stock returns are lower on days around a full moon than on days around a new moon.

Two caveats are in order. First, although psychological studies have been conducted under both ambient and outdoor temperatures, in today's world, most dwellings and office buildings are equipped with cooling and heating systems such that indoor temperature is kept within a comfortable range. If anything, it is the temporary exposure to (e.g., walking outside when it is very hot or cold) and the psychological imprint of the extreme temperature that mediates people's mood and influences their behavior. In this sense, temperature should affect investors' behavior no less than the amount of sunshine (Hirshleifer and Shumway, 2003), since traders work indoors, and, in many cases, in windowless trading rooms. Second, to our knowledge, there is no psychological literature that directly examines the impact of weather variables on investment behavior. As other finance researchers have done in this field, we extrapolate from mood to investment behavior. Regardless, mood-induced stock return patterns seem to contradict market efficiency. It is for this reason that we call the linkage between temperature and stock returns an "anomaly".

2. Data, empirical tests and results

Our investigation is based on nine international stock indices, covering eight financial markets located in the US, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan. The stock index data are retrieved from Datastream, and the temperature data are from the Earth Satellite Corporation (EarthSat). While the stock index data are available for many markets in the world, the scope of the temperature data is restricted by the availability from EarthSat. In the end, the above eight markets are chosen with joint considerations of the availability of temperature data, maturity of the market, and geographical representation around the globe. The sample period varies across markets with July 3, 1962 being the earliest starting date and July 9, 2001 the latest ending date.

All non-US indices are broad based, value-weighted indices with the exception of the OMX index of Sweden which consists of 30 stocks on the Stockholmsbörsen with the largest trading volume measured in Swedish kronor. In order to uncover the potential difference in temperature effects with different weighting schemes, we consider both the equal-weighted and the value-weighted indices (CRSP) for the US.

The temperature variable is the average of the daily maximum and minimum temperatures, which we simply refer to as "daily temperature". After matching the daily temperatures with returns, Sweden has the smallest sample size of 3129 while the US has the largest of 9442. We call these "full samples" since they cover each market's longest possible period. To facilitate seemingly unrelated regressions and to ensure comparability of results, we also create "equal-size" samples by matching indices and temperatures across all markets within the common sample period, which is from January 2, 1989 to December 31, 1999. The equal-size sample has 2252 observations.

We implement two types of tests. First, following Saunders (1993), we group returns according to temperature ordering and calculate a z-score to assess the statistical difference between return-groups. We call this the "bin test", which is semi-parametric in nature. Second, similar to Hirshleifer and Shumway (2003), and Kamstra et al. (2003), we perform regression tests to quantify the precise linkage between temperature and stock returns while controlling for other known anomalies such as the Monday effect and tax-loss selling effect.

2.1. Bin tests—uncovering correlation between temperature and returns

For each location, we first sort the matched data by temperature in ascending order, and then divide the temperature series into bins. For each temperature bin, we calculate the mean return and the frequency or percentage of positive returns. [3] We then compare the mean returns associated with the two bins covering the lowest and the highest temperatures, and determine whether the difference in mean returns is significant. In order to see if the return difference between bins is driven by outliers, similar comparisons and tests are done for the percentage of positive returns of the two extreme bins. If, for example, lower temperature is indeed associated with higher stock returns, then we would expect that the higher returns in the low temperature bin are broadly based. In other words, we would expect the percentage of positive returns to be high in the low temperature bin.

The precise testing procedure is as follows. First, we compute the difference between the maximum and minimum of the temperature series, and divide the difference by the number of bins, k to obtain the temperature range of each bin. That is, $\Delta = \frac{\text{Temp}_{\max} - \text{Temp}_{\min}}{k}$. The first bin contains temperatures in the range $[\text{Temp}_{\min}, \text{Temp}_{\min} + \Delta)$; the second bin contains temperatures in the range $[\text{Temp}_{\min} + \Delta, \text{Temp}_{\min} + 2\Delta)$;... and so on.

To determine whether the mean returns associated with the highest temperature bin (i.e., bin k) and the lowest temperature bin (i.e., bin 1) are significantly different, we follow Saunders (1993) to compute the following z-statistic:

$$z\_\text{score}_{k,1}^{\text{mean}} = \frac{\mu_k - \mu_1}{\sqrt{\sigma_k^2/n_k + \sigma_1^2/n_1}}$$

where μ_i, σ_i^2 and n_i stand for the mean return, the variance of return and the number of observations of bin i ($i = 1$ or k). A similar z-statistic is calculated to determine whether the frequencies of positive returns are significantly different between the two extreme bins:

$$z\_\text{score}_{k,1}^{\text{frequence}} = \frac{p_k - p_1}{\sqrt{p_k(1 - p_k)/n_k + p_1(1 - p_1)/n_1}}$$

where p_i stands for the percentage of positive returns in bin i ($i = 1$ or k).

We first perform the tests on the full sample as a preliminary check, and then perform the tests on the equal-size sample for cross-market comparisons. In both cases, we set the number of bins equal to 2, 3, 4, and 5. As the number of bins increases, the

[3] Returns are always expressed in percentage forms throughout this paper.

number of observations within each bin decreases. For brevity and reliability, we only report the results for the 4-bin case. [4] Table 1 contains the results.

Panel A of Table 1 (full sample) shows a strong negative correlation between temperature and stock returns. For all stock markets, the lower the temperature, the higher the returns and the more likely that stocks will experience a positive price change. All the relationships are generally monotonic. Statistically, five out of the eight markets exhibit *z*-scores significant at the 10% for either the mean comparison or the positive return comparison, or both. When we combine all the indices, the relationship remains. For both combinations involving the CRSP equal-weighted and value-weighted indices, the *z*-scores are all significant at the 1% level. This means that there is universal negative correlation between temperature and stock returns.

For Australia, the *z*-score is significant at the 5% level and the ranking of mean returns and frequencies of positive returns is generally monotonic. This is a very important observation in that the same season actually covers different calendar months on the Northern and Southern Hemispheres. It means that temperature is a common factor to the stock market returns.

Moreover, Panel A shows that the temperature impact is much stronger on the CRSP equal-weighted index. It appears that prices of small-cap stocks respond to investors' mood change in a much more pronounced fashion. Nonetheless, it is comforting to realize that what we have uncovered is not driven by a few small-cap stocks. The phenomenon appears to apply equally well to large-cap stocks, since most indices are broadly based and valued-weighted.

So far, our observations are based on unequal samples covering different time periods. In order to make valid cross-market comparisons, we need to examine the equal-size sample. Panel B of Table 1 contains the bin test results. With only a few exceptions, the *z*-scores are lower than those in the full sample due to fewer observations. The *z*-score for mean comparisons is significant at the 1% level for the US (CRSP equal-weighted) and Canada, 5% level for Taiwan, and 10% level for Sweden. The *z*-score for the CRSP value-weighted index is no longer significant, which again reflects the dominance of small-cap stocks in mood impacts. Remarkably, even with a shorter sample period, the general monotonic patterns remain in mean returns and frequencies of positive returns. For markets other than the US, Canada, Sweden and Taiwan, there is also a negative correlation and the *z*-scores are generally very different from zero (e.g., Germany and Australia). Similar to the full sample case, when all indices are combined the *z*-scores are all significant at the 1% level.

The results in Table 1 confirm our hypothesis that lower temperature is associated with higher returns. We can also infer that apathy must dominate aggression in risk-taking under higher temperature since a negative correlation is also present when the temperature is high. To what extent does aggression weaken the negative correlation under higher temperature? To address this question, we divide the equal-size sample into two seasons, winter and summer, and perform the bin test for each season.

[4] The results for the 2-bin and 3-bin cases are generally stronger than those for the 4-bin case.

Table 1
Relation between temperature and stock market returns—overall correlation

		Panel A: Full sample					Panel B: Equal-size sample				
		Bin 1	Bin 2	Bin 3	Bin 4	z-score(4, 1)	Bin 1	Bin 2	Bin 3	Bin 4	z-score(4, 1)
US CRSP-EW	Return mean	0.2407	0.1198	0.0354	0.0503	−5.7841***	0.2257	0.1326	0.0865	0.0668	−2.5777 ***
	% of + returns	0.7086	0.6195	0.5925	0.5993	−4.4179***	0.7632	0.6559	0.6454	0.6356	−2.4263**
US CRSP−VW	Return mean	0.1299	0.0727	0.0291	0.0442	−2.1234**	0.1222	0.1127	0.0337	0.0198	−1.1335
	% of + returns	0.6222	0.5529	0.5297	0.5566	−2.5058**	0.6184	0.5632	0.5400	0.5624	−0.9450
Canada	Return mean	0.0932	0.0396	0.0110	0.0450	−1.0837	0.1574	0.0229	0.0327	−0.0115	−2.8293**
	% of + returns	0.6053	0.5443	0.5252	0.5483	−2.0781**	0.5789	0.5448	0.5478	0.5327	−0.9226
Britain	Return mean	0.1726	0.0628	0.0083	0.0426	−1.4814	0.1216	0.0555	−0.0017	0.0396	−0.8205
	% of + returns	0.5909	0.5296	0.5189	0.5540	−0.7518	0.5100	0.5192	0.5129	0.5482	0.6387
Germany	Return mean	0.1813	0.0670	−0.0063	0.0122	−2.4452**	0.1442	0.0815	−0.0364	0.0035	−1.2190
	% of + returns	0.5650	0.5312	0.5020	0.5174	−1.3921	0.5215	0.5420	0.5183	0.5136	−0.1677
Sweden	Return mean	0.2224	0.1321	0.0305	−0.0212	−1.2501	0.4019	0.1531	0.0153	−0.0069	−1.8486*
	% of + returns	0.5625	0.5528	0.5069	0.5231	−0.5300	0.6176	0.5551	0.5039	0.5389	−0.9106
Australia	Return mean	0.0548	0.0047	0.0812	−0.1495	−2.0768**	0.0590	0.0338	−0.0009	−0.0885	−1.2442
	% of + returns	0.5384	0.5096	0.5487	0.4839	−0.9993	0.5329	0.5134	0.5249	0.5072	−0.3993
Japan	Return mean	0.0643	0.0090	−0.0082	−0.0491	−1.7406*	−0.0067	−0.0165	0.0022	−0.1103	−0.9978
	% of + returns	0.5442	0.5077	0.5103	0.4902	−2.2080**	0.5021	0.4993	0.5014	0.4709	−0.9193
Taiwan	Return mean	0.2007	0.1456	0.0433	−0.0031	−0.6810	0.3318	0.0756	0.0498	−0.1645	−2.3359**
	% of + returns	0.5000	0.5336	0.5323	0.5065	0.0185	0.5688	0.5093	0.4974	0.4785	−1.7831*
CRSP-EW with other indices	Return mean	0.1608	0.0926	0.0255	0.0219	−4.1985***	0.1937	0.0900	0.0314	−0.0166	−3.8099***
	% of + returns	0.6342	0.5654	0.5320	0.5364	−5.2808***	0.6281	0.5543	0.5282	0.5171	−3.1954***
CRSP-VW with other indices	Return mean	0.1465	0.0742	0.0249	0.0204	−3.7618***	0.1975	0.0809	0.0278	−0.0198	−3.9020***
	% of + returns	0.6203	0.5444	0.5220	0.5268	−5.0122***	0.6181	0.5382	0.5194	0.5100	−3.0951***

Notes. (1) This table reports bin-test results for the full sample and the equal-size sample. The length of the full sample varies across markets; that of the equal-size sample covers the period of 1989–1999 with 2252 observations. We report the mean return and the percentage of positive returns for each of the four bins, and the z-scores.

(2) $z\_\text{score}^{\text{mean}}_{4,1} = (\mu_4 - \mu_1)\Big/\sqrt{\frac{\sigma_4^2}{n_4}+\frac{\sigma_1^2}{n_1}}$ and $z\_\text{score}^{\text{frequence}}_{4,1} = (p_4 - p_1)\Big/\sqrt{\frac{p_4(1-p_4)}{n_4}+\frac{p_1(1-p_1)}{n_1}}$, where μ^i and σ^i are the return mean and standard deviation for bin i = 1, 4; p^i is the percentage of positive returns and n^i is the number of observations in bin i ($i = 1, 4$).

(3) The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).

Following the industry convention, we group the days from May 1 to September 30 into the summer season, and the rest into the winter season. [5] The table is omitted for brevity.

Comparing the results with Panel B of Table 1, we have fewer significant z -scores in both seasons. The smaller sample size clearly reduces the testing power. Nonetheless, with only a few exceptions, the negative correlation between temperature and stock returns is present for all markets in both seasons. It is also present when all indices are combined for each season. Judging by the number of significant z-scores and the overall size of all z-scores, the correlation is slightly stronger in the winter than in the summer, which is consistent with our priors based on the psychological literature reviewed earlier. On a whole, the results indicate that apathy strongly dominates aggression in the summer, and as a result, there is an overall negative correlation between temperature and stock returns for the entire temperature range.

2.2. Regression analysis—controlling for known anomalies

The bin tests can only establish an association between temperature and returns. They cannot measure the precise correlation; nor can they control for some of the known anomalies in stock returns. In this section, we perform regression analyses to gain further insights. Similar to Kamstra et al. (2003), we correct for the first-order auto-correlation in returns, the Monday effect and the tax-loss effect. Specifically, we run the following regression:

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{\text{Mon}} + \alpha_4 D_t^{\text{Tax}} + \alpha_5 \text{Temp}_t + \varepsilon_t, \qquad (2.1)$$

where r_t is the daily return at time t for a given index; D_t^{Mon} is a dummy variable which equals 1 for Mondays and 0 otherwise; D_t^{Tax} is a dummy variable which equals 1 for the first 10 days of the taxation year and 0 otherwise; Temp_t is the daily temperature, and ε_t is the error term. The tax year starts on April 6 in Britain, July 1 in Australia and January 1 in all other jurisdictions.

As in the case of bin tests, we first run the OLS regression in (2.1) for the full sample as a preliminary check. Panel A of Table 2 reports the results. For brevity, we only focus on the temperature variable. With the exception of Canada and Australia, all markets have a negative coefficient that is significant at the 10% level. Some are significant at the 5% and 1% levels. The R^2 is relatively higher for the US and Canada. In terms of pattern and magnitude, the R^2 across markets is very similar to that in Kamstra et al. (2003).

In order to take into account the inter-market correlations and perform joint tests on the temperature coefficients, we use the equal-size sample to run a seemingly unrelated regression (SUR). We conduct two chi-square tests on the temperature coefficients. The first test, determining if all the coefficients are jointly different from zero,

[5] In the weather derivatives industry, the summer season usually covers months from May to September, and the winter season from November to March. April and October are referred to as "shoulder months". We include them in the winter season because the weather in those two months is cool for most of the locations we consider. Of course, the summer for Australia is from November to March.

Table 2
Regressions analysis with monday dummy, tax-dummy and temperature

$$r_1 = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{\mathrm{Mon}} + \alpha_4 D_t^{\mathrm{Tax}} + \alpha_5 \mathrm{Temp}_t + \varepsilon_t$$

	Panel A: individual regression with full-sized sample					Panel B: SUR test of equal-size sample with CRSP-VW					
	α_2	α_3	α_4	α_5	R^2	α_2	α_3	α_4	α_5	α_5'	R^2
US CRSP-EW	0.3809	−0.3054	0.1798	−0.0021	0.1723						
	40.0903	−18.7260***	5.1848***	−3.0669***							
US CRSP-VW	0.1713	−0.1471	0.0350	−0.0016	0.0344	−0.0356	0.0110	−0.0978	−0.0026	−0.0040	0.0078
	16.9216	−6.9822***	0.7822	−1.7319*		−2.1613	0.2425	−1.1120	−1.5744	−2.1995**	
Canada	0.1900	−0.1327	−0.0165	−0.0014	0.0394	0.0820	−0.0289	−0.0228	−0.0016	−0.0030	0.0353
	15.1222	−4.8211***	−0.2894	−1.3369		4.9958	−0.7270	−0.2891	−1.2047	−2.1041**	
Britain	0.0725	−0.1080	0.0086	−0.0051	0.0079	−0.0167	−0.0834	0.0392	−0.0024	−0.0048	0.0060
	4.7544	−2.8099***	0.1081	−1.9127*		−0.9978	−1.6377	0.5530	−0.8300	−1.4676	
Germany	0.0418	−0.1408	0.0575	−0.0037	0.0050	−0.0281	−0.0264	−0.1093	−0.0038	−0.0072	0.0033
	3.7201	−4.4329***	0.8647	−2.1243**		−1.6971	−0.3685	−0.8959	−1.1928	−1.9836**	
Sweden	0.0615	0.0380	0.0462	−0.0077	0.0060	−0.0276	−0.0477	0.0939	−0.0069	−0.0081	0.0079
	3.4503	0.5928	0.3409	−2.2936**		−1.6352	−0.6302	0.7071	−2.1514**	−2.2252**	
Australia	0.0849	−0.0491	0.1755	0.0011	0.0089	0.0233	−0.0451	0.0394	−0.0050	−0.0043	0.0024
	5.4867	−1.2330	2.1635**	0.2700		1.2515	−0.9240	0.4797	−1.2051	−0.9532	
Japan	0.0039	−0.1195	−0.0906	−0.0047	0.0019	−0.0050	−0.2719	−0.0040	0.0009	−0.0033	0.0052
	0.2537	−2.2788**	−0.7475	−1.7409*		−0.2615	−3.2034***	−0.0238	0.2253	−0.7821	
Taiwan	0.1003	−0.1263	0.0075	−0.0074	0.0114	−0.0082	−0.0123	−0.3169	−0.0278	−0.0292	0.0062
	8.1519	−2.2780**	0.0655	−1.9177*		−0.3991	−0.1083	−1.3272	−3.4841***	−3.6295***	
System-wide R^2									0.0054		
$\chi2(8)$									21.8217^^^		
$\chi2(7)$									15.3690^^		

Notes. (1) This table reports regression analysis of both the full sample (OLS regressions) and the equal-size sample (SUR—seemingly unrelated regression). We control for first-order autocorrelation (r_{t-1}), the Monday effect (D_t^{Mon}), and the tax-loss effect (D_t^{Tax}). The tax dummy (D_t^{Tax}) covers the first 10 trading days of the taxation year. The taxation year starts on April 6 in Britain, July in Australia, and January 1 in all other jurisdictions.

(2) For each market, the first row contains the parameter estimates, and the second contains the *t*-values. For brevity and clarity, we omit the intercept estimate and only indicate the significance for explanatory variables $D_t^{\mathrm{Mon}}, D_t^{\mathrm{Tax}}$, and Temp_t. The last column of each panel contains the R^2 of individual OLS regressions. The system-wide R^2 is for seemingly unrelated regressions.

(3) The column with heading α_5' contains the coefficients and *t*-values of the temperature variable Temp_t from individual regressions using the equal-size sample.

(4) The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test). The first chi-square statistic with 8 degrees of freedom is for testing if all temperature coefficients are equal to zero, while the second statistic with 7 degrees of freedom is for testing if all temperature coefficients are equal. The carets ^, ^^, and ^^^ indicate statistical significance at the 10%, 5%, and 1% levels respectively.

helps us to establish whether the negative correlations (between temperature and stock returns) are jointly significant after controlling for inter-market correlations. The second test, determining whether all coefficients are equal, helps to ascertain if investors in different markets react to the same temperature change to the same degree. To facilitate comparisons, we also perform OLS regressions using the equal-size sample. Panel B of Table 2 reports the regressions for the CRSP value-weighted index together with all other indices. We omit the CRSP equal-weighted counterpart of Panel B, since the results are very similar. In addition, for brevity, we only report the temperature variable's coefficient estimate, its t-value, and the R^2 from the individual regressions. For the seemingly unrelated regressions, we report the system-wide R^2.

The temperature coefficient from OLS regressions is negative for all markets, and significant at the 5% level or higher for US, Canada, Germany, Sweden and Taiwan. The t-value for Britain is nearly significant at the 10% level. Unlike in the full sample, Australia now has a negative coefficient, albeit not significant. The t-values are generally lower for the seemingly unrelated regressions, and there are several cases (e.g., Germany) where the t-value is significant in the OLS regression but not in the SUR. This is due to the positive inter-market correlations. Only Sweden and Taiwan have a t-value significant at the 10% level or higher. However, the chi-square statistic for the first test is significant at the 1%, meaning that the negative correlation between temperature and stock returns is jointly significant across all markets. The chi-square statistic for the second test is significant at the 5% level, implying that, although the negative association between temperature and stock returns is universal, it is not uniform across markets. Investors in different temperature domiciles react to temperature changes in the same way, but to different extents.

At this point, it is useful to know if the temperature effect is still present after controlling for some nature-related anomalies, in addition to the ones just considered. As mentioned before, Saunders (1993), and Hirshleifer and Shumway (2003) both found that stock returns are positively related to the amount of sunshine or, equivalently, negatively related to cloud cover. Kamstra et al. (2003) found that seasonal affective disorder (SAD) plays a role in the seasonal variation of stock market returns, and in general, lower stock returns are related to longer nights.

To control for the nature-related anomalies, we add to regression (2.1) two more explanatory variables: Cloud_t (cloud cover) and SAD_t, the latter being the number of night hours minus 12 for the period of September 21 to March 20, and zero otherwise. The augmented regression takes the following form:

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{\mathrm{Mon}} + \alpha_4 D_t^{\mathrm{Tax}} + \alpha_5 \mathrm{Temp}_t + \alpha_6 \mathrm{Cloud}_t + \alpha_7 \mathrm{SAD}_t + \varepsilon_t. \tag{2.2}$$

Again, to correct for inter-market correlations and to ensure comparability, we use the equal-size sample to run SUR as well as individual regressions.

As in Hirshleifer and Shumway (2003), our cloud cover data are obtained from the NCDC, and we also use the "total sky cover" to measure cloud cover which is the hourly average from 6:00 am to 4:00 pm. The variable "total sky cover" ranges in value from 0 (clear) to 8 (overcast). Canada, Germany, and Japan are eliminated from the sample since the sky cover observations are not complete for Toronto, Frankfurt and Tokyo. Further matching the cloud cover data with the equal-size sample reduces the overall sample size to 1903. Table 3 reports the mean and standard deviation of cloud cover for each market, and the regression results.

Individual OLS regressions in Panel B reveal that, after controlling for the cloud cover and SAD effects, the temperature coefficient remains negative for all markets and the t-values are significant at the 5% level for US (CRSP equal-weighted index), Sweden and Taiwan. The coefficients for Cloud_t and SAD_t are generally negative and are significant only for the CRSP equal-weighted index. Therefore, in terms of statistical significance, the temperature variable exhibits the strongest effect on returns. The cloud cover results and the SAD effect are consistent with the findings of Hirshleifer and Shumway (2003), and Kamstra et al. (2003).

The relative sizes of the three coefficients are not the same across markets. For instance, the magnitude of the temperature coefficient is the largest for Taiwan but the smallest for Australia. The range of the temperature variable is several-fold wider than those of the cloud cover and the SAD variables. To gain some insights on the economic significance of the temperature effect, we examine how much the daily return reacts to, say, one standard deviation shock in the temperature. [6] For instance, the standard deviation of daily temperature in New York is 9.62 °C, and the temperature coefficient is −0.0031 for the value-weighted CRSP index. The one-standard-deviation impact of temperature on the return is therefore 0.029%, which is slightly bigger than one half of the average daily return, 0.051%. Similarly, the temperature impact is about one and half times the daily average return for Sweden, and four times of the daily average return for Taiwan.

The SUR results are very similar to the individual OLS regression results, as shown in Panels C and D. More importantly, the chi-square tests reveal that the temperature coefficients are jointly different from zero at the 1% level (Panel C) and 5% level (Panel D), while the cloud cover and SAD coefficients are not statistically different from zero. Moreover, the temperature coefficients are statistically different at the 1% level, broadly consistent with the results in Table 2. The results in Table 3 convincingly show that, statistically, the impact of temperature on stock market returns is much stronger than those of the amount of sunshine and the length of the night.

2.3. Auxiliary analyses

We have also performed a series of robustness tests and we omit the tables for brevity. We list the tests below and discuss the results briefly. First, to analyze the robustness to distributional assumptions, we conducted two nonparametric tests: the Spearman's rank correlation test and the Friedman's two-way analysis of variance. The previous results hold up under both tests.

[6] We thank an anonymous referee for suggesting this analysis.

Table 3
Explanatory power of temperature, cloud cover, and the SAD variable

$$r_1 = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{\mathrm{Mon}} + \alpha_4 D_t^{\mathrm{Tax}} + \alpha_5 \mathrm{Temp}_t + \alpha_6 \mathrm{Cloud}_t + \alpha_7 \mathrm{SAD}_t + \varepsilon_t$$

	Panel A: cloud cover		Panel B: individual test			
	Mean	Standard deviation	Temp_t	Cloud_t	SAD_t	R^2
US CRSP-EW	4.749	2.734	−0.0033	−0.0071	−0.0136	0.0969
			−2.1301**	−1.7372*	−1.8128*	
US CRSP-VW	4.749	2.734	−0.0031	−0.0087	−0.0043	0.0064
			−1.4022	−1.4677	−0.3990	
Britain	5.832	1.889	−0.0025	−0.0082	0.0022	0.0069
			−0.5947	−0.8207	0.2452	
Sweden	5.309	1.955	−0.0112	−0.0018	−0.0158	0.0113
			−2.2182**	−0.1211	−1.5335	
Australia	3.812	2.320	−0.0019	−0.0051	−0.0100	0.0025
			−0.3372	−0.6462	−0.5898	
Taiwan	5.432	1.918	−0.0292	0.0093	0.0156	0.0071
			−2.4412**	0.3513	0.2603	

	Panel C: SUR test with US CRSP-EW			Panel D: SUR test with US CRSP-VW		
	Temp_t	Cloud_t	SAD_t	Temp_t	Cloud_t	SAD_t
US CRSP-EW	−0.0031	−0.0035	−0.0144			
	−2.1699**	−0.9833	−1.9742**			
US CRSP-VW				−0.0031	−0.0045	−0.0037
				−1.4463	−0.8309	−0.3467
Britain	0.0009	−0.0058	0.0068	0.0000	−0.0060	0.0055
	0.2438	−0.6880	0.7922	−0.0024	−0.7122	0.6342
Sweden	−0.0106	−0.0073	−0.0149	−0.0114	−0.0086	−0.0159
	−2.3610**	−0.5864	−1.5239	−2.4859**	−0.6744	−1.6091
Australia	−0.0022	−0.0048	−0.0094	−0.0022	−0.0048	−0.0094
	−0.3871	−0.6099	−0.5582	−0.3871	−0.6099	−0.5582
Taiwan	−0.0279	0.0101	0.0185	−0.0284	0.0097	0.0172
	−2.3613	0.3825	0.3093	−2.3968**	0.3704	0.2884
System-wide R^2			0.0158			0.0052
$\chi^2(5)$	16.0862^^	2.2798	8.9246	14.5477^^	2.1876	4.7706
$\chi^2(4)$	25.3057^^^	0.7712	7.9253^	17.5363^^^	0.7263	4.6070

Notes. (1) Cloud_t measures the cloud cover, and SAD_t is the number of night hours minus 12 for the period of September 21 to March 20, and zero otherwise; The number of night hours is calculated as $7.72 \cdot \arccos[-\tan(2\pi\delta/360)\tan(\lambda_t)]$ for the Southern Hemisphere, and 24 minus this quantity for the Northern Hemisphere. In the above, δ is the latitude of the market location, and $\lambda_t = 0.4102 \cdot \sin[(2\pi/360)](\text{julian} - 80.25)]$ where "*julian*" represents the day of the year, i.e., julian = 1 for January 1, 2 for January 2, and so on.
(2) For brevity, we only report the coefficients and t-values for Temp_t, Cloud_t, and SAD_t. The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test).
(3) The tax dummy, D_t^{Tax} covers the first ten trading days of the taxation year. The taxation year starts on April 6 in Britain, July 1 in Australia, and January 1 in all other jurisdictions.
(4) The chi-square statistic with 5 degrees of freedom is for testing if all coefficients for each explanatory variable are equal to zero. The second chi-square statistic with 4 degrees of freedom is for testing if all coefficients are equal. The carets ^, ^^, and ^^^ indicate statistical significance at the 10%, 5% and 1% levels respectively.

Second, we performed bin tests and regressions on daily temperature deviations. A temperature deviation is the difference between daily temperature and the historical average daily temperature. A positive deviation means a warmer-than-normal day and a negative deviation means the opposite. The absolute level of temperature may capture its overall seasonal impacts on returns, while the temperature deviations can capture the impact of daily temperature shocks. Our tests confirmed that the relationship between temperature and stock market returns is a manifestation of the day-to-day impacts of temperature shocks.

Third, to provide some evidence on the intertemporal stability of the relationship between temperature and returns, we repeated the analyses for sub-samples of the US market. By and large, the relationship between temperature and market returns is quite stable over sub-sample periods.

Fourth, to address the concern that investors may spread over a much larger region than the city where the exchange resides, we calculated a population-weighted temperature index based on seven major US cities from coast to coast, and repeated the bin tests and regressions using the temperature index. The overall results remain unchanged.

Lastly, to further ascertain the validity of our conclusions across all international markets, we performed tests on an expanded sample which covers all the locations studied by Hirshleifer and Shumway (2003) and Kamstra et al. (2003). We found that the negative correlation between temperature and returns is prevalent across all markets even after controlling for other known anomalies.

3. Summary and conclusion

It is well established in the psychological literature that mood, feelings and emotions affect people's decision-making, and mood itself can be influenced by environmental factors such as weather conditions. A body of psychological literature shows that temperature is one of the important meteorological variables affecting people's mood, and the affected mood in turn regulates behavior. Evidence suggests that low temperature tends to cause aggression, and high temperature tends to cause aggression, hysteria, and apathy. It is only natural to conjecture that temperature variations would cause investors to alter their investment behavior.

Research to date has revealed that stock market returns are associated with nature-related variables and events such as the amount of sunshine (Saunders, 1993; Hirshleifer and Shumway, 2003), the daylight-savings time change (Kamstra et al., 2000), the length of the night (Kamstra et al., 2003), and the lunar phases of the moon (Dichev and Janes, 2001; Yuan et al., 2001). Based on psychological and clinical evidence, these authors conjectured and hypothesized that investors' mood is affected by the above meteorological variables and the mood change causes them to alter their investment behavior.

In this study we attempt to identify the relationship between temperature and stock market returns. The existing psychological evidence seems to suggest that lower temperature can cause aggression, and higher temperature can cause apathy as well as aggression. We therefore hypothesize that lower temperature leads to higher stock returns due to investors' aggressive risk-taking, and higher temperature can lead to higher or lower stock returns since aggression and apathy have competing effects on risk-taking.

After examining more than twenty international markets, out of which eight are examined in depth, we have indeed uncovered a temperature anomaly. Our analysis reveals an overall negative correlation between temperature and stock market returns. The impact of apathy dominates that of aggression in the summer, leading to a statistically significant, negative correlation across the whole temperature range. The correlation is robust to alternative tests (parametric, semi-parametric, and nonparametric) and remains present after controlling for such known anomalies as the Monday effect, the tax loss effect, the cloud cover effect, and the seasonal affective disorder effect.

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