Stock Market Returns: A Temperature Anomaly *

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Abstract

This study investigates whether stock market returns are related to temperature. Psychological research has shown that temperature significantly affects mood, and mood changes, in turn, lead to behavioral changes. It is known 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. After examining many stock markets world-wide, we find a statistically significant, negative correlation between temperature and returns across the whole range of temperature. Apathy dominates aggression when the temperature is high. We therefore observe an overall negative relation between temperature and stock return. The observed negative correlation is robust to alternative tests and retains its statistical significance after controlling for various known anomalies.

Keywords: stock market returns, stock market anomalies, temperature anomaly.

JEL classifications: G14, G10, G15.

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Abstract

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1. Introduction

It has long been recognized in the literature that mood, feelings and emotions play an important role in making decisions and forming judgments. For instance, Schwarz (1990), and Loewenstein, Weber, Hsee and Welch (2001) provided theories linking mood and feelings to general decision-making, while Etzioni (1988), Romer (2000), and Hanock (2002) established the importance of emotions in economic decision-making. Mehra and Sah (2002) showed theoretically that the emotional state of investors will influence equity prices when investors' subjective parameters such as risk-aversion change in response to mood fluctuations.

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; and 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, Lesko and Garrett, 1980; Bell, 1981; Sanders and Bizzolara, 1982; Howarth and Hoffman, 1984; Rind, 1986; Watson, 2000; Parsons, 2001; and Pilcher, Nadler and Busch, 2002). Researchers hypothesize that weather conditions affect mood or induce misattributed mood, which in turn regulates behavior. The typically studied weather variables include the amount of sunshine, precipitation, humidity, temperature, wind speed and direction, and barometric pressure.

In a comprehensive study encompassing all the aforementioned 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, Nadler and Busch (2002).[2] Wyndham (1969) found behavioral changes in the form of hysteria and apathy under extreme heat. Meantime, Cunningham (1979), and Schneider, Lesko and Garrett (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; and Howarth and Hoffman, 1984) have gathered evidence that suggests increased level of aggression at high ambient temperature. By the same token, Schneider, Lesko and Garrett (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.[3]

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. The central premise of behavioral finance is that individuals are not always rational and their decision making is influenced by their mood or emotional state.[4] If weather conditions affect mood or cause mood misattribution, then they will influence investors' risk aversion and risk assessments, which in turn affect their investment behavior.

Saunders (1993) was the first to link investment behavior to weather conditions. Focusing on

[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.

[2] A meta-analysis essentially aggregates individual samples from different studies and perform mathematical analysis on the combined sample. Their analysis covered 22 primary studies involving 317 participants in total.

[3] On an application level, Parsons (2001) found a negative relation between shopping traffic and the maximum temperature.

[4] For illuminating examples and insightful discussions, please see Johnson and Tversky (1983), and Thaler (1991); for broader discussions and analysis, please see Thaler (1993).

the City of New York, he demonstrated a linkage between cloud cover and stock market returns. For the sample period of 1927 - 1989, Saunders first grouped all days into bins according to the extent of cloud cover. He then calculated the average returns for each bin for three indices: the DJIA index, the NYSE/AMEX value-weighted index, and the NYSE/AMEX equal-weighted index. He found that less cloud cover is associated with higher returns, and the return difference between the bin with the most cloud cover and that with the least cloud cover is statistically significant. Since cloud cover and the amount of sunshine are antithetic variables, 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 and inferences were confirmed by Hirshleifer and Shumway (2003) who examined 26 stock market indices around the globe for the period of 1982 - 1997. For most indices, a positive correlation is found between the amount of sunshine and daily returns.

Recently, Kamstra, Kramer and Levi (2000), by examining stock markets in the United States, Canada, the United Kingdom, and Germany, found that the stock market returns are substantially lower on the weekends coinciding with the daylight-savings time changes. Citing evidence from desynchronosis literature, they postulated that the disruption of sleep patterns around the time change would impair judgment and raise anxiety, which would, in turn, cause investors to seek for safety and avoid risk-taking. Such a change in behavior would lead to depressed stock prices. In a subsequent study, Kamstra, Kramer and Levi (2003) examined the impact of Seasonal Affective Disorder (SAD) on stock market returns. Based on the broad 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.

Finally, two groups of authors (Dichev and Janes, 2001; and Yuan, Zheng and Zhu, 2001) independently documented a relationship between lunar phases and stock market returns. While

Dichev and Janes (2001) focused on the U.S. market only, Yuan, Zheng and Zhu (2001) examined 48 international markets in depth. After removing the usual anomalies such as the January effect and the day-of-the-week effect, they showed that stock returns are much lower on days around a full moon than on days around a new moon.

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, which in turn affects behavior. Just as the amount of sunshine or the length of the night affect investors' behavior by altering their mood and psychological state, we expect a similar linkage between temperature and market returns. Our research therefore complements the aforementioned enquires. Similar to Saunders (1993), and Hirshleifer and Shumway (2003), we relate a stochastic variable, i.e., daily temperature, to stock returns. In contrast, Dichev and Janes (2001), Yuan, Zheng and Zhu (2001), and Kamstra, Kramer and Levi (2003) relate deterministic cyclical variables to stock 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 the temperature is high, apathy dominates aggression, resulting in lower returns. Nevertheless, a statistically significant, overall negative correlation exists between temperature and stock returns. We show that this correlation is prevalent among stock markets around the globe. The correlation is robust to various alternative tests and specifications, and it remains strong even after controlling for the geographical dispersion of investors relative to the city where the stock exchange resides.

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 directly contradict rational thinking and market efficiency. It is for this reason that we call the linkage between temperature and stock returns an "anomaly", in much the same way we dub the small-firm effect or day-of-the-week effect.

The rest of the paper is organized as follows: Section 2 presents the primary data and summary statistics for eight international stock markets; Section 3 reports the empirical relation between temperature and stock returns while controlling for various known anomalies; Section 4 presents auxiliary and robustness analyses including tests on an expanded sample covering additional stock markets around the world; Section 5 provides a brief summary and concluding remarks. Tables and figures are collected at the end of the paper.

2. Data

Our primary empirical investigation is based on nine international stock indices, covering eight financial markets in North America, Europe, Asia and Australia. The eight markets are located in the United States, Canada, Britain, Germany, Sweden, Australia, Japan and Taiwan. The stock index data are retrieved from Datastream, and the temperature data are purchased from the Earth Satellite Corporation (EarthSat).[5] 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 the temperature data, the maturity of the market, and the geographical representation around the globe. In the auxiliary investigations presented in Section 4, we expand the data set to include locations studied by Hirshleifer and Shumway (2003), and Kamstra, Kramer and Levi (2003). For those additional locations, the temperature data are from the National Climatic Data Denter (NCDC) which cover a shorter period and are of low quality in terms of completeness and accuracy.

Table 1 presents the stock exchanges, city locations, weather stations, and summary statistics for the eight primary locations. All non-U.S. indices are broad based, value-weighted indices with the exception of the OMX index of Sweden which is a value-weighted index consisting of 30 stocks with the largest volume of trading measured in Swedish kronor on the Stockholmsbörsen. Using value-weighted indices allows us to avoid the potential dominance of small-cap stocks in detecting investors' reaction to temperature changes. In order to uncover the potential difference in temperature effects with the two weighting schemes, we consider both the equal-weighted and the value-weighted indices for the United States.

For the temperature variable, we follow the meteorological convention and use the average of the daily maximum and minimum temperatures as a measure of the daily temperature. For brevity, we will simply call this daily average temperature the "daily temperature". For a given sample period, we always have more observations for temperature than for returns since the latter can only be observed for trading days. We therefore eliminate temperature observations for holidays and weekends so that the two series are matched for each market. After matching, Sweden has

[5] EarthSat's home page: http://www.earthsat.com.

the smallest sample size of 3129 while the U.S. has the largest sample size of 9442. We will call these "full samples" since they cover each market's longest possible period in our data set. To facilitate seemingly unrelated regressions and to ensure comparability of results, we also create "equal-size" samples by matching all indices and temperatures across markets within the common sample period, which is from January 2, 1989 to December 31, 1999. The equal-size samples have 2252 observations for each market.

The temperature mean ranges from 6.97°C in Stockholm, Sweden to 22.81°C in Taipei, Taiwan. The standard deviation of daily temperature ranges from 4.10°C in Sydney, Australia to 10.59°C in Toronto, Canada. The lowest temperature was -24.70°C in Toronto while the highest temperature was 34.44°C in New York. For most of the cities, the temperature series exhibit a negative skewness, indicating that it is more common to have extremely cold days than extremely hot days.

To illustrate the temperature progressions throughout the calendar year, we plot the historical average daily temperature for four cities in Figure 1: New York, London, Sydney and Tokyo.[6] For cities on the Northern Hemisphere, seasonal temperature changes are similar, though the range of variations can be quite different. Naturally, an opposite pattern is observed for Sydney which is on the Southern Hemisphere. It is clear from Figure 1 and Panel B of Table 1 that Sydney has the smallest seasonal variation in temperature.

For daily returns, the mean ranges from 0.005% for Nikkei 225 to 0.075% for the CRSP equal-weighted index. The standard deviation varies across indices, with Taiwan Weighted being the most volatile at 1.675% and the CRSP equal-weighted index the least volatile at 0.682%. The largest single-day loss was -28.71%, experienced in Australia during the October 1987 crash. The largest single-day gain was 13.14%, experienced in Sweden on November 19, 1992. All index returns, except that for OMX in Sweden, are negatively skewed. All return series exhibit a strong kurtosis.[7]

[6] "Historical average daily temperature" refers to the average of daily temperatures for each calendar day in the sample period. There are 366 such averages, including February 29 in leap years.

[7] Returns and standard deviations are always expressed in percentage forms throughout this paper.

3. Empirical Tests and Results

We implement two types of tests to investigate the relationship between temperature and stock market returns. 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 due to the ordering procedure. Second, similar to Hirshleifer and Shumway (2003), and Kamstra, Kramer and Levi (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.

3.1. Bin Tests – Uncovering Correlation between Temperature and Returns

For each stock market location, we first sort the matched data by temperature in ascending order, and then divide the temperature series into sub-groups or bins. For each temperature bin, we calculate the mean return and the frequency or percentage of positive returns. We then compare the mean returns associated with the lowest bin (i.e., the bin covering the lower spectrum of the temperature range) and the highest bin (i.e., the bin covering the higher spectrum of the temperature range), and determine whether the difference in mean returns is significant. Similar comparisons and tests are done for the percentage of positive returns of the two extreme bins. The purpose of examining the frequency of positive returns is to see if the return difference between bins is driven by outliers. If, for example, lower temperature is indeed associated with higher stock returns and vice versa, 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. Then, we divide the difference by the number of bins, k to obtain the temperature range of each bin. That is, $\Delta = \frac{Temp_{\max} - Temp_{\min}}{k}$. The first bin contains temperatures in the range $[Temp_{\min}, Temp_{\min} + \Delta)$; the second bin contains temperatures in the range $[Temp_{\min} + \Delta, Temp_{\min} + 2\Delta)$; ... and so on. For example, if the maximum and minimum temperatures are 24 and -3, respectively, and the number of bins is 3, then the first bin will contain temperatures ranging from -3 to 6, the second bin ranging from 6 to 15, and the third ranging from 15 to 24.

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:

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

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:

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

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

Based on a similar reasoning given by Saunders (1993), we argue that potential heteroscedasticity in the variance estimators used to construct the z statistic should be largely absent for two reasons. First, the heteroscedasticity in the variance for the frequency of positive daily returns is ruled out because the variable measures a binomial outcome. Second, it is unlikely that the variance for daily percentage returns is heteroscedastic because the observations are grouped by temperature, a random exogenous factor. In daily or monthly return time series, heteroscedasticity is often present, as documented by French, Schwert and Stambaugh (1987) and Schwert (1989). In our study, return variances for all the bins in each test are very close, as evident in Table 2.

The above calculations and tests are done for the nine market indices. 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 number of observations within each bin decreases. For brevity and reliability, we only report the results for the 3-bin and 4-bin cases.[8] Table 2 contains the results, with Panel A presenting the full sample, and Panel B the equal-size sample.

Panel A of Table 2 shows a strong negative correlation between temperature and stock returns. For all stock markets, the lower the temperature, the higher the returns; and this relationship is generally monotonic, especially for the 3-bin case. When the number of bins is set to three, the z statistics of mean return comparisons for all markets other than Canada and Taiwan are significant at the 10% level, with some being significant at the 5% and 1% levels.[9] For Canada and Taiwan, the z statistics for frequencies of positive returns are both significant at the 5%. In general, the lower the temperature, the more likely that stocks will experience a positive price change. The results are generally weaker when we set the number of bins to four. This is expected since the testing power decreases as we increase the number of bins. But even with four bins, 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 strictly monotonic for the 3-bin case. This is a very important

[8]The results for the 2-bin case are generally stronger than those for the 3- or 4-bin cases. So the omission of the 2-bin results will only err on the side of caution.

[9]Although we have a strong prior that an overall negative correlation exists between temperature and stock returns, we employ two-tail tests throughout the paper in order to be conservative. Please note that, for one-tail tests at the 10% significance level, the critical z-score or t-value for a large enough sample is 1.282.

observation in that the same season actually covers different calendar months on the Northern and Southern Hemispheres. It is seen in Figure 1 that temperatures progress in opposite directions on the two hemispheres. The observations for Australia convincingly imply that temperature is a common factor to the stock market returns.

Another observation relates to equal-weighted versus value-weighted indices. 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 in our sample are broadly based and valued-weighted.

So far, our observations and discussions are based on unequal samples covering different time periods. In order to make valid comparisons between markets, we need to examine the equal-size sample which not only covers the same time period, but also has the same number of observations for all markets. Panel B of Table 2 contains the bin test results. With only a few exceptions, the z-scores are lower than those for the full sample due to fewer observations. In both tests (3-bin and 4-bin), the z-score is significant at the 5% level for three markets (U.S., Canada and Taiwan), and significant at the 10% level for one market (Sweden). The significance level for Canada and Taiwan is actually higher than that of the full sample. 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 both the 3-bin case and the 4-bin case. In sum, within the same sample period, U.S. (CRSP equal-weighted index), Canada, Sweden and Taiwan exhibit a statistically significant, negative correlation between temperature and stock returns. Other markets also exhibit a negative correlation and the z-scores are generally very different from zero (e.g., U.S.–CRSP equal-weighted index, Britain and Australia). Similar to the full sample case, when all indices are combined the z-scores are all significant at the 1% level.

The bin test results in Table 2 have revealed an overall negative correlation between temperature and returns. The results certainly confirm our hypothesis that lower temperature is associated with higher returns. We can also infer that such a negative correlation must be present when the temperature is high, i.e., apathy must dominate aggression in risk-taking under higher temperature. The question is: 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. 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.[10] Table 3 presents the results.

Comparing with Panel B of Table 2, we now see fewer significant z-scores in both seasons. The smaller sample size for each season 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. One exception is Canada, where the correlation is actually stronger in the summer according to the 3-bin test. On a whole, Table 3 indicates 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. For brevity and clarity, we will only present the overall results in the remainder of the paper.

[10]In the weather derivatives industry, financial contracts are usually written on cooling-degree-days (CDDs) and heating-degree-days (HDDs), which are essentially temperature deviations from the "comfort level" defined to be 65°F or 18.3°C. The CDD season covers months from May to September, and the HDD 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. The test results for the winter season remain more or less unchanged when we exclude these two months. Of course, the summer of Australia is from November to March.

3.2. Regression Analysis – Controlling for Known Anomalies

The bin tests can only establish an association between temperature and returns. They can not 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, Kramer and Levi (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,

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \varepsilon_t, \tag{3.1}$$

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 at time t, and ε_t is the residual 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 (3.1) for the full sample as a preliminary check. Panel A of Table 4 reports the results. To begin with, returns on Mondays are lower for all markets with the exception of Sweden and Australia. This Monday effect is significant at the 1% level for U.S., Canada, Britain, and Germany, and it is significant at the 5% for Japan and Taiwan. In contrast, the tax loss effect is significant for only U.S. and Australia, and it has the right sign for all markets with the exception of Canada and Japan.[11]

As for 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 significant, negative coefficient for most markets is consistent with the bin test results. The temperature coefficient for Canada is negative and the t -value is nearly significant at the 10% level. For Australia, the coefficient is positive but close to zero in significance. The R^2 is relatively

[11]In this and all other tests that follow, we have repeated the regressions using a 5-day or one-month window for the tax-loss dummy. All results are similar.

higher for the U.S. and Canada. In terms of pattern and magnitude, the R^2 across markets is very similar to that in Kamstra, Kramer and Levi (2003).

The full sample results are only preliminary for several reasons. First, the sample periods are different among markets, making valid comparisons difficult; second, the returns and temperatures are correlated among markets, casting doubt on the validity of the OLS regressions; third, we cannot perform joint tests of the temperature variable's significance across markets. To address these concerns, we use the equal-size sample to run a seemingly unrelated regression (SUR) for all the markets using the specification in (3.1). This regression takes into account the inter-market correlations and, at the same time, allows us to perform a joint test on the temperature coefficients. We conduct two chi-square tests on the temperature coefficients. The first test, determining if all the coefficients are jointly different from zero, helps us to establish whether the negative correlations (between temperature and stock returns) observed for individual markets 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 4 reports the regressions for the CRSP equal-weighted index together with all other indices, and Panel C is the CRSP value-weighted index counterpart of Panel B. 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 U.S., 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 a significant one. As for the seemingly unrelated regressions, we see that the t-values are generally lower than those from the individual OLS regressions. There are several cases (e.g., Germany) where the t-value is significant in the OLS regression but not in the SUR. This is to be expected due to the positive inter-market correlations. Only U.S. (CRSP equal-weighted index), 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% level in both panels. This means 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 in both panels. We can therefore infer 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.

To this point, we have established that there is a strong negative correlation between temperature and stock returns even after controlling for auto-correlation in returns, the Monday effect and the tax-loss effect. It is useful to know if the temperature effect is still present after controlling for some known nature-related anomalies. 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, Kramer and Levi (2003) found that seasonal affective disorder (SAD) plays a role in the seasonal variation of stock market returns. Among other things, they found that stock returns are closely related to the length of the night in the fall and the winter. In general, lower stock returns are found to be related to longer nights.

To control for the above additional anomalies, we expand the regression in (3.1) by adding 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:

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \alpha_6 Cloud_t + \alpha_7 SAD_t + \varepsilon_t. \qquad (3.2)$$

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 6:00am to 4:00pm. 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.[12] Since the cloud cover data are available for the period of 1982 to 1997 and the equal-size sample is from 1989 to 1999, further matching reduces the overall sample size to 1903. Table 5 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 U.S. (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 confirm the findings of Hirshleifer and Shumway (2003), namely, higher stock returns are related to sunny days. They also found that the regression coefficient tends to be negative for most cities, though it is rarely significant. As for the length-of-the-night variable, SAD_t, our results are consistent with the findings of Kamstra, Kramer and Levi (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 variable and the SAD variable. 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.[13] For instance, the standard deviation of daily temperature in New York is 9.62

[12]Hirshleifer and Shumway (2003) had similar exlusions in the their study. As mentioned earlier and further discussed in Section 4, the temperature data from NCDC are also incomplete and inaccurate for certain locations.

[13]We thank an anonymous referee for sugegsting this analysis.

degrees Celsius, 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 4. The results in Table 5 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.

All told, the regression analyses reveal a statistically significant, negative relationship between temperature and stock market returns even after controlling for the first order auto-correlation in returns, the Monday effect, the tax loss effect, the cloud cover effect, and the length-of-the-night effect. The statistical significance obtains in both the individual OLS regressions and the seemingly unrelated regressions which control for inter-market correlations. To further strengthen our results and conclusions, we now turn to some additional tests.

4. Auxiliary Analyses

4.1. Nonparametric Tests

So far, all the tests are either semi-parametric (bin tests) or completely parametric (regression tests). It is helpful to know whether our previous analyses are robust to distributional assumptions. To this end, we perform two nonparametric tests, with one testing the general correlation between temperature and stock returns, and the other testing whether investors react to the same temperature change to the same extent. The first, Spearman's rank correlation test, is roughly a nonparametric counterpart of the bin test, but is stronger and more precise; the second, Friedman's two-way analysis of variance, is the nonparametric counterpart of the chi-square test in SUR that tests if all the temperature coefficients are equal.

Unlike the usual Pearson's correlation which requires the data series to be normally distributed, the Spearman's correlation is based on the ranks of the two data series in question and is therefore distribution-free. The precise formula is $\rho_s = 1 - \left[6 \sum_{i=1}^{n} d_i^2\right] / \left[n(n^2 - 1)\right]$ where ρ_s is the Spearman's rank correlation, n is the number of observations, and d_i is the rank difference for the ith observation. When the number of observations is larger than 10, ρ_s has a t-distribution with $n-2$ degrees of freedom, and the test statistic is given by $t = \rho_s^2 \sqrt{(n-2)/(1 - \rho_s^2)}$.

To avoid spurious correlations, we calculate Spearman's correlation based on temperature bins. Table 1 reveals that the maximum temperature range is about 50 degrees. We therefore put temperatures into 50 bins and calculate the mean temperature and return for each bin. A rank correlation is then calculated using the mean temperatures and returns. For robustness check, we also use 30, 40, 60, 70 and 100 bins. The rank correlation is calculated for each individual market and all the markets combined. Panel A of Table 6 reports the results.

When the number of bins is 40, 50 or 60, correlations for all the markets (except Australia) are significant at the 10% level or higher. Although not significant, the correlation for Australia is negative. With a bin size of 50, the correlation for all markets combined is significant at the 1% level (two-tailed test) when the CRSP equal-weighted index is used, and significant at the 5% level when the CRSP value-weighted index is used. Although the size of the correlations decreases as the number of bins increases (which is a common feature of most time series), the significance remains more or less unchanged.

We now turn to the second nonparametric test. The regression analyses indicate that investors in different temperature domiciles react to temperature changes to different extents. We would like to ascertain if this result holds up to nonparametric tests. We design the test in the following way.[14] We first create temperature bins common to all markets; we then test if returns are equal across markets within each temperature bin or range. This joint test essentially allows us to determine if investors react to the absolute levels of temperature, or to the levels relative to the local norm. In other words, it helps to answer the following question: Does a temperature range of, say 5°C to 8°C induce the same reaction among investors around the globe? Intuition would suggest a negative answer since a cool temperature in one place may be perceived as a warm temperature in another, depending on the local year-round average temperature.

The Friedman's two-way analysis of variance is an ideal choice for our test. Let k be the number of markets and n be the number temperature bins. The Friedman's test statistic is then calculated as $\frac{12}{kn(k+1)} \sum_{j=1}^{k} S_j^2 - 3n(k+1)$, where S_j is the sum of ranks received by the jth market.[15] This statistic has a chi-square distribution with $(k-1)$ degrees of freedom. Since this is a joint test, we again have two versions of the combination, depending on whether we use the CRSP equal-weighted index or the CRSP value-weighted index for U.S.. In addition, we must choose a common temperature range applicable to all markets. Table 1 indicates that the lowest maximum temperature among all the markets is 26.70°C (Sweden), and the highest minimum temperature is 8.15°C (Australia). We therefore set 8.15°C as the lower bound and 26.70°C as the upper bound. Temperature bins are created within this range. The chi-square statistics and their significance are reported in Panel B of Table 6.

With up to five temperature bins, the chi-square statistic is significant at the 5% or 10% level, indicating that investors around the globe do not react to the same temperature level to the same extent. In other words, a universal temperature-level effect does not exist across markets. This is

[14] We would like to thank an anonymous referee for suggesting the initial idea which led to our design and for suggesting nonparametric tests in the first place.

[15] The ranking is for the mean returns of all the markets within each temperature bin. An average rank is assigned when ties are present.

consistent with the chi-square test on the temperature coefficients from SUR. When the number of temperature bins is greater than five, the chi-square statistics are no longer significant. With a large number of bins, the temperature range within each bin is too narrow (e.g., it is only $[26.7 - 8.15]/6 = 3.09°C$ with six bins) to pick up return differences.

Overall, our nonparametric tests indicate that, regardless of distributional assumptions and inter-market correlations, a negative correlation between temperature and stock returns exists for individual markets and for all markets combined. Our bin tests and regression analyses are therefore quite robust.

4.2. Tests based on temperature deviations

All the tests so far show a very strong negative relation between returns and temperature. It is of interest to see whether a similar relation exists between returns and temperature deviations, the latter being 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.

Since deviations reflect whether a particular day is warmer or colder than normal, and since very cold days are in the winter and very hot days are in the summer, we will combine positive deviations for the summer and negative deviations for the winter to perform joint analyses. This approach has three advantages: 1) it uses both positive and negative deviations, 2) it covers the whole year, and 3) it emphasizes the impact of temperature deviations most relevant for the season. Again, we use the equal-size sample for comparability. As evident in Figure 1, the plot of historical average daily temperatures is not very smooth, due to the relatively short sample period. (Keep in mind that even for the longest sample (U.S.), there are only 37 observations for each day of the year.) To smooth the historical average daily temperatures, we calculate moving averages of the historical averages using window sizes of 3, 7, 15, and 31 days. We create two versions of the daily moving average, depending on whether the current day is placed in the middle or at the end of the moving window. As shown in Figure 2 (using New York as an example), including more days in the moving window leads to a smoother curve, as one would expect. With various versions of the daily average, we calculate daily temperature deviations and use them to perform bin tests as in Table 2 and regressions as in (3.1). For brevity, we only report the temperature coefficient and its t-value from OLS regressions. The results are reported in Table 7.[16]

The temperature coefficient is negative for all markets and all sizes of moving windows. The only exception is Japan when the moving window is 15 days. The negative coefficient is significant at the 10% level for U.S. (CRSP equal-weighted index), and significant at the 1% level for Taiwan. The results do not seem to be sensitive to the smoothing of daily average temperatures, and the R^2 is largely comparable to that in Table 4 for each regression. Overall, the correlation is understandably weaker in terms of statistical significance since we have removed the level effect. Nonetheless, the consistent sign across markets does imply a negative relation between temperature deviations and stock returns.

The above results confirm that the relationship between temperature and stock market returns is a manifestation of the day-to-day impacts of temperature shocks, as opposed to a reflection of purely seasonal effects. Subtracting the historical average from the realized temperatures amounts to removing any seasonal effects; what remains belongs to the realm of daily impacts. This is a significant point in that, just like the impact of sunshine, the temperature can exert psychological impacts on investors on a daily basis. The correlation between market returns and daily, season-adjusted temperature variations is the ultimate confirmation of temperature impact on investors' behavior.

[16] We could not perform SUR since the signs of temperature deviations for a particular day do not always coincide across markets, making data matching very difficult. Moreover, the bin test results are consistent with the regression results in that all z-scores are negative and some are significant. Finally, when the current day is placed at the end of the moving window, the test results remain more or less unchanged.

4.3. Sub-sample results

To provide some evidence on the intertemporal stability of the relationship between temperature and returns, we repeat the analyses for sub-samples. We will focus on the U.S. market since the time series have the longest sample period. As shown in Table 1, the sample starts on July 3, 1962. To utilize all observations and to ensure rough equality between sub-samples, we cut the entire sample into three sub-periods corresponding to 1962 - 1974, 1975 - 1987, and 1988 - 1999, with the last sub-period approximately matching the equal-size sample period. Bin tests and OLS regression analyses are performed for each sub-sample and each index. By and large, the qualitative relationship between temperature and market returns is quite stable. Quantitatively, the estimated coefficients do not necessarily stay constant over time. To demonstrate this point, we report the regression results in Table 8. It is seen that, for both indices, the coefficient for the temperature variable seems to be on the rise. This is just by chance since sub-sample analyses for other markets failed to produce similar results.

Incidentally, as evident in the t-values and the R^2, the Monday effect, the tax effect and the temperature effect are all stronger in the equal-weighted index than in the value-weighted index for all sub-samples, consistent with the observations from previous tables.

4.4. Aggregating temperature impacts across regions

We recognize that trades of a particular stock need not be always executed on the floor of the exchange. Stock price movements are due to trading actions of both local brokers / investors and market participants elsewhere. For instance, the trading registered on the NYSE is driven by investors in the city of New York and elsewhere. Conceivably, investors in other parts of the United States may be subject to quite a different weather condition. Therefore, as with the sunshine study of Hirshleifer and Shumway (2003), our study so far is subject to the question of investor concentration in the city which houses the stock exchange. Thankfully, unlike cloud cover or the amount of sunshine, temperatures tend to be highly correlated across regions. An indirect way to measure the aggregate temperature impact on market returns is to calculate the correlation between the average temperature across different regions and the national stock market index. This is the route we take. We identify seven major cities in the U.S. which represent the key regions of the country: Atlanta, Chicago, Dallas, Los Angeles, New York, Philadelphia, and Seattle. The daily temperature data for all cities other than New York come from NCDC, which cover the period from January 1, 1982 to December 31, 1997. Two aggregate temperature indices are constructed, with the first being a simple, equally-weighted average of the seven temperature series, and the second being a population-weighted average.[17] Bin tests and regression analyses are then performed using the CRSP indices and the aggregate temperature indices. Table 9 reports the results.

It is seen that the general results for New York city alone from Table 2 (Panel A) and Table 4 (Panel A) also apply here, albeit the statistical significance for most estimates is now lower. It should be realized that the reduction in significance is not simply due to the use of a temperature index. A shorter sample period is undoubtedly another contributing factor, as is evident in Table 2. Nonetheless, a statistically significant, negative correlation between temperature and returns is largely preserved. For instance, three of the z-scores for mean return comparisons under three bins are significant at the 1% level, and one at the 5%. The t-value for the temperature coefficient from regression analyses is significant at the 5% level for the CRSP equal-weighted index, and is far from zero for the CRSP value-weighted index.

The above observations imply that our empirical findings are not subject to the criticism that the city housing the stock exchange may not represent the entire population of investors. While investors are scattered around the country, they are subject to very similar temperature variations because of the high correlations among regional temperatures.[18]

[17] We use population as a proxy for investor concentration. The population data are taken from the 1998 census: Atlanta (425,022), Chicago (2,802,079), Dallas (1,075,894), Los Angelas (3,597,556), New York (7,420,166), Philadelphia (1,436287), and Seattle (536,978).

[18] For instance, the correlation between daily temperatures of New York and Chicago is 0.8964. See Cao and Wei

4.5. Tests on an Expanded Sample

To further ascertain the validity of our conclusions across all international markets, we perform tests on an expanded sample which covers all the locations studied by Hirshleifer and Shumway (2003) and Kamstra, Kramer and Levi (2003). Combining the locations in the two studies and subtracting the locations in our existing sample, we come up with a list of 21 additional cities. Bangkok and Brussels are deleted from the list due to severe errors in the temperature data. We therefore end up with 19 additional locations as shown in Table 10 which contains summary statistics. As in Hirshleifer and Shumway (2003), for most cities, we use the Datastream Global Index as the market index, while for several other cities (Helsinki, Kula Lumpur, Madrid, Manila, Rio de Janeiro, and Santiago), we use the local market indices which cover a longer sample period. The temperature and cloud cover data are from the NCDC.

The NCDC data set is restricted to the period of 1982 to 1997. The starting date for some market indices is after 1982. Table 10 shows the overlapping sample period for each location. In contrast to the market index data, the temperature data are typically not complete (i.e., with many missing observations) and sometimes contain errors (e.g., some temperatures are higher than 300 degrees Celsius). After deleting the obvious erroneous observations for each location, we end up with the number of observations as shown in Table 10.[19] As in previous analyses, for comparability, we date-match all the additional locations together with the existing ones. The overlapping sample period is from 1989 to 1997, and the number of matched observations is 1509.

We first perform bin tests on this expanded, equal-size sample. Table 11 contains the results (for brevity, we omit the return standard deviation for each bin / city). Several observations are

(2003) for other properties of daily temperatures.

[19]The temperature data have other problems too. Typically, the recording frequency is every 30 minutes, although it can be as frequent as every 15 minutes. But the total number of observations can vary a great deal from one day to the next. If, for a particular day, the available data points do not cover the true range of the daily temperature (e.g., if they were all recorded around noon), then the average of the recorded maximum and minimum will be a biased estimate of the true average temperature for the day.

The shorter sample period (1982 - 1997) and the aforementioned problems are the two reasons for us to treat the analysis on the expanded sample as auxiliary.

in order. First, comparing the top portion of Table 11 with Panel B of Table 2, we see a drop in significance for the eight locations we previously examined. This is mainly due to the lower testing power associated with a smaller sample (1509 vs. 2252). Nevertheless, with the exception of Japan (3-bin), the z-score for the bin return comparison is negative for all locations, confirming the previously observed negative correlation between temperature and returns.

Second, for the nineteen additional markets, seven have a negative and significant z-score under the 3-bin test and five under the 4-bin test. Most of the z-scores are negative, confirming a negative correlation between temperature and returns. Remarkably, the z-score for Auckland is negative and significant for both the 3-bin and 4-bin tests. The 3-bin z-score is also significant for Australia. The results for the two markets residing on the South Hemisphere once again confirm the universal negative association between temperature and returns.[20]

Third, the negative correlation is also observed for the combined sample. For return comparisons, the 4-bin z-scores are significant at the 5% level for both combinations involving either the CRSP-EW index or the CRSP-VW index, while the 3-bin z-score are nearly significant at the 10% level. For comparisons of percentages of positive returns, the 3-bin and 4-bin z-scores are all significant at the 1% level for both combinations.

As with the primary sample, in order to control for other anomalies, we perform regression tests on the expanded sample. We could perform two sets of regressions as for the primary sample, one with temperature only and the other with temperature as well as cloud cover and SAD. As shown earlier, regression (3.1) is in favour of the temperature variable thanks to a longer sample period and the absence of competing variables. To preserve space and to be on the conservative side, we only report the results from regression (3.2). To facilitate SUR, we need to further match the data including the cloud cover. In this process, Rio de Janeiro is dropped from the sample since it has too

[20] It is interesting to observe that the less significant z-scores (both negative and positive) tend to be associated with locations closer to the equator, or locations with small temperature variations. This is another piece of evidence confirming the temperature impacts on stock market returns.

few cloud cover observations in common with other locations, and the matched sample would have only 355 observations. After date-matching all locations (dropping Rio de Janeiro) with respect to return, temperature and cloud cover, we end up with an equal-size sample of 1013 observations for 23 markets. Table 12 reports the regression results involving only the value-weighted CRSP index for the U.S..[21]

First and foremost, for SUR, the temperature coefficient is negative for 21 of the 23 markets, and the t-values for five coefficients are significant at the 10% level or higher. The two chi-square statistics are significant at the 5% and 10% levels respectively. For individual regressions, the temperature coefficient is positive for only one market (Malaysia). It is evident that, the negative correlation between temperature and returns is prevalent across markets even after controlling for other known anomalies.

The SAD effect also appears strong in the expanded sample, although none of the chi-square statistics is significant. The SAD coefficient is negative for most of the cities. This negative association between returns and the length of the night confirms the general findings of Kamstra, Kramer and Levi (2003) who examined nine markets.

As for the sunshine effect, the cloud cover coefficient is negative for many cities, consistent with the findings of Hirshleifer and Shumway (2003). However, the coefficient is positive and statistically significant for three cities under either the individual or SUR tests. Therefore, after controlling for temperature and SAD effects, the sunshine effect is no longer uniform across all locations.

By now we have shown that there is indeed a "temperature anomaly" in stock markets around the globe. Specifically, a statistically significant, negative correlation exists between temperature

[21] Again, this is for brevity and conservativeness. Recall from Table 5 that the SUR results involving the two CRSP indices are largely similar and those with the equally weighted CRSP index are slightly stronger.

We have also performed the Spearman's rank correlation test on the additional 19 locations. With 50 bins, 9 of the 19 correlations (most negative) are significant, comparable to the bin test results in Table 11. We did not perform the Friedman's test since the common temperature range among all cities is too narrow.

and stock returns. The relation is robust to many alternative tests and remains present after controlling for various known anomalies.

5. 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. It is known 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, Kramer and Levi, 2000), the length of the night (Kamstra, Kramer and Levi, 2003), and the lunar phases of the moon (Dichev and Janes, 2001; and Yuan, Zheng and Zhu, 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. For instance, longer nights in the winter cause depression on the part of investors, who would become more risk-averse and shun risk-taking, the overall result of which is lower stock returns for days with very long nights (Kamstra, Kramer and Levi, 2003).

In this study we follow a similar line of reasoning and 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.

References

[1] Allen, A. M. and G. J. Fisher, 1978, "Ambient Temperature Effects on Paired Associate Learning", Ergonomics, 21(2), 95-101.

[2] Baron, R.A. and V.M. Ransberger, 1978, "Ambient Temperature and the Occurrence of Collective Violence: The Long, Hot Summer Revisited", Journal of Personality and Social Psychology, 36, 351-360.

[3] Bell, P. A. and R. A. Baron, 1976, "Aggression and Heat: The Mediating Role of Negative Affect", Journal of Applied Social Psychology, 6, 18-30.

[4] Bell, P.A., 1981, "Physiological Comfort, Performance and Social Effects of Heat Stress", Journal of Social Issues, 37, 71-94.

[5] Cao, M. and J. Wei, 2003, "Weather Derivatives Valuation and Market Price of Weather Risk", Working Paper, York University and University of Toronto, Canada.

[6] Clore, Gerald L. and W. Gerrod Parrot, 1991, "Moods and Their Vicissitudes: Thoughts and Feelings as Information", in Joseph P. Forgas (ed.), Emotion and Social Judgements (107-123). Pergamon Press, Oxford.

[7] Cummingham, M. R., 1979, "Weather, Mood and Helping Behavior: Quasi-Experiment with the Sunshine Samaritan", Journal of Personality and Social Psychology, 37, 1947-1956.

[8] Dichev, I. D. and T. D. Janes, 2001, "Lunar Cycle Effects in Stock Returns", Working Paper, University of Michigan.

[9] Etzioni, Amitai, 1988, "Normative-Affective Factors: Towards a New Decision-Making Model", Journal of Economic Psychology, 9 (2), 125-150.

[10] French, K. R., Schwert, G. W. and R. F. Stambaugh, 1987, "Expected Stock Returns and Volatility", Journal of Financial Economics, 19, 3-29.

[11] Hanock, Yaniv, 2002, " 'Neither an Angel nor am Ant': Emotion as an Aid to Bounded Rationality", Journal of Economic Psychology, 23 (1), 1-25.

[12] Hirshleifer, D. and T. Shumway, 2003, “Good Day Sunshine: Stock Returns and the Weather”, Journal of Finance, 58 (3).

[13] Howarth E. and M. S. Hoffman, 1984, “A Multidimensional Approach to the Relationship between Mood and Weather”, British Journal of Psychology, 75, 15-23.

[14] Johnson, E. J. and A. Tversky, 1983, “Affect, Generalization, and the Perception of Risk”, Journal of Personality and Social Psychology, 45, 20-31.

[15] Kamstra, M. J., L. A. Kramer, and M. D. Levi, 2000, “Losing Sleep at the Market: the Daylight-Savings Anomaly”, American Economic Review, 90(4), 1005-1011.

[16] Kamstra, M. J., L. A. Kramer, and M. D. Levi, 2003, “Winter Blues: A SAD Stock Market Cycle”, American Economic Review, 93 (1), 324-333.

[17] Loewenstein, George F., Elke U. Weber, Christopher K. Hsee, and Ned Welch, 2001 “Risk as Feelings”, Psychological Bulletin, 127 (2), 267-286.

[18] Mehra, R. and R. Sah, 2002, “Mood Fluctuations, Projection Bias and Volatility of Equity Prices”, Journal of Economic Dynamics and Control, 26, 869-887.

[19] Moos, R. H. 1976, “The Human Context: Environmental Determinants of Behaviors”, Wiley, New York.

[20] Palamerek, D. L. and Rule, B. G., 1980, “The Effects of Ambient Temperature and Insult on the Motivation to Retaliate or Escape”, Motivation and Emotion, 3, 83-92.

[21] Parsons, Andrew G., 2001, “The Association Between Daily Weather and Daily Shopping Patterns”, Australasian Marketing Journal, 9 (2), 78-84.

[22] Pilcher, June J., Eric Nadler and Caroline Busch, 2002, “Effects of Hot and Cold Temperature Exposure on Performance: A Meta-Analytic Review”, Ergonomics, 45 (10), 682-698.

[23] Rashes, M. S., 2001, “Massively Confused Investors Making Conspicuously Ignorant Choices”, Journal of Finance, forthcoming.

[24] Rind, B., 1996, “Effects of Beliefs about Weather Conditions on Tipping”, Journal of Applied Social Psychology, 26, 137-147.

[25] Romer, P. M., 2000, "Thinking and Feeling", American Economic Review, 90 (2), 439-443.

[26] Sanders, J. L. and M. S. Brizzolara, 1982, "Relationship between Mood and Weather", Journal of General Psychology, 107, 157-158.

[27] Saunders, E. M. J., 1993, "Stock Prices and Wall Street Weather", American Economic Review, 83, 1337-1345.

[28] Schneider, F. W., Lesko, W. A. and W. A. Garrett, 1980, "Helping Behavior in Hot, Comfortable and Cold Temperature: A Field Study", Environment and Behavior, 2, 231-241.

[29] Schwarz, Norbert and Gerald L. Clore, 1983, "Mood, Misattribution, and Judgements of Well-being: Informative and Directive Functions of Affective States", Journal of Personality and Social Psychology, 45, 513-523.

[30] Schwarz, Norbert, 1990, "Feelings as Information: Informational and Motivational Functions of Affective States", in E. Tory Higgins and Richard M. Sorrentino (eds.), Handbook of Motivation and Cognition (Vol 2, 527-561). Guilford Press, New York.

[31] Schwert, G. W., 1989, "Why Does Stock Market Volatility Change Over Time?", Journal of Finance, 44, 1115-1153.

[32] Thaler, R., 1991, "The Winner's Curse: Paradoxes and Anomalies of Economic Life", Free Press.

[33] Thaler, R., 1993, "Advances in Behavioral Finance", editor, Russell Sage Foundation.

[34] Watson, David, 2000, "Situational and Environmental Influence on Mood", Chapter 3 of Mood and Temperament, Guilford Press, New York.

[35] Wyndham, H. C., 1969, "Adaptation to Heat and Cold", Environmental Research, 2, 442-469.

[36] Yuan, K., L. Zheng and Q. Zhu, 2001, "Are Investors Moonstruck? Lunar Phases and Stock Returns", Working Paper, University of Michigan.

Table 1: Stock Exchanges, Locations, and Summary Statistics for Returns and Temperatures

Country / State	UnitedStates		Canada	Britain	Germany	Sweden	Australia	Japan	Taiwan
Index	CRSP-EW	CRSP-VW	TSE 300	FTSE 100	DAX 100	OMX	All Ordinaries	Nikkei 250	Taiwan Weighted
City	New York	New York	Toronto	London	Frankfurt	Stockholm	Sydney	Tokyo	Taipei
Latitude	$41^0$46'N	$41^0$46'N	$43^0$41'N	$51^0$29'N	$50^0$03'N	$50^0$21'N	$33^0$57'S	$35^0$41'N	$25^0$02'N
Beginning	07/03/1962	07/03/1962	01/04/1977	04/03/1984	01/06/1970	01/02/1989	08/06/1984	01/05/1984	10/01/1977
Ending	12/31/1999	12/31/1999	03/13/2001	03/13/2001	07/09/2001	06/29/2001	12/31/2000	07/09/2001	07/09/2001
				Panel A: Daily Return (%)					
# of obs.	9442	9442	6099	4285	7901	3129	4145	4314	6777
Mean	0.075	0.051	0.036	0.038	0.028	0.054	0.036	0.005	0.037
Std. Dev.	0.682	0.821	0.850	0.985	1.124	1.426	1.012	1.364	1.675
Min	-10.484	-17.173	-12.010	-13.029	-13.706	-7.491	-28.713	-16.135	-9.710
Max	6.944	8.669	8.650	7.597	8.862	13.142	5.739	12.430	7.581
Skewness	-1.11	-1.12	-1.13	-0.99	-0.48	0.32	-6.16	-0.12	-0.27
Kurtosis	16.98	26.22	16.47	13.90	8.05	6.20	162.38	9.17	2.81
				Panel B: Daily Temperature (Celsius)					
# of obs.	13696	13696	8835	6189	11508	4558	5992	6396	8373
Mean	12.71	12.71	7.61	11.23	10.08	6.97	18.30	16.34	22.81
Std. Dev.	9.62	9.62	10.59	5.67	7.41	7.78	4.10	7.91	5.50
Min	-16.39	-16.39	-24.70	-7.55	-14.20	-20.95	8.15	-0.90	-1.55
Max	34.44	34.44	30.35	27.40	29.30	26.70	32.00	33.40	34.00
Skewness	-0.19	-0.19	-0.23	-0.02	-0.11	-0.08	0.11	0.06	-0.32
Kurtosis	-0.89	-0.89	-0.82	-0.60	-0.65	-0.65	-0.65	-1.15	-0.85

Note:
1.Daily returns are in percentage forms. For example, the mean return for Britain is 0.038%.
2.Weather stations for each city:
New York: New York Laguardia Airport, Toronto: Toronto International Airport,
London: London Heathrow Airport, Frankfurt: Frankfurt Main Airport,
Stockholm: Stockholm / Bromma Airport, Sydney: Sdyney International Airport,
Tokyo: Tokyo Airport, Taipei: Sungshan / Taipei Airport.

Table 2: Relation Between Temperature and Stock Market Returns – Overall Correlation

Panel A: Full Sample

		# of bins = 3				# of bins = 4				
		bin 1	bin 2	bin 3	z-score(3,1)	bin 1	bin 2	bin 3	bin 4	z-score(4,1)
U.S. CRSP-EW	Return Mean	0.2000	0.0775	0.0340	-7.4261 ***	0.2407	0.1198	0.0354	0.0503	-5.7841 ***
	Std. Dev. of Return	0.6403	0.7234	0.6306		0.6074	0.6674	0.7253	0.6358	
	% of Positive Returns	0.6780	0.6079	0.5868	-5.5041 ***	0.7086	0.6195	0.5925	0.5993	-4.4179 ***
U.S. CRSP-VW	Return Mean	0.0917	0.0556	0.0330	-2.3042 **	0.1299	0.0727	0.0291	0.0442	-2.1234 **
	Std. Dev. of Return	0.7104	0.8703	0.7807		0.7441	0.7596	0.8981	0.7805	
	% of Positive Returns	0.5855	0.5432	0.5428	-2.4684 **	0.6222	0.5529	0.5297	0.5566	-2.5058 **
Canada	Return Mean	0.0705	0.0292	0.0249	-1.4287	0.0932	0.0396	0.0110	0.0450	-1.0837
	Std. Dev. of Return	0.8179	0.9186	0.7697		0.8101	0.8922	0.8852	0.7477	
	% of Positive Returns	0.5737	0.5414	0.5304	-2.1973 **	0.6053	0.5443	0.5252	0.5483	-2.0781 **
Britain	Return Mean	0.1570	0.0197	0.0363	-2.3702 **	0.1726	0.0628	0.0083	0.0426	-1.4814
	Std. Dev. of Return	0.9149	1.0299	0.8877		0.8780	0.9602	1.0284	0.8920	
	% of Positive Returns	0.5702	0.5187	0.5375	-1.1737	0.5909	0.5296	0.5189	0.5540	-0.7518
Germany	Return Mean	0.1100	0.0206	0.0189	-2.0186 **	0.1813	0.0670	-0.0063	0.0122	-2.4452 **
	Std. Dev. of Return	1.0836	1.1644	1.0648		1.0010	1.1301	1.1680	1.0201	
	% of Positive Returns	0.5385	0.5135	0.5167	-1.0454	0.5650	0.5312	0.5020	0.5174	-1.3921
Sweden	Return Mean	0.2189	0.0826	-0.0143	-2.1230 **	0.2224	0.1321	0.0305	-0.0212	-1.2501
	Std. Dev. of Return	1.2851	1.5271	1.2580		1.3085	1.4561	1.4896	1.2240	
	% of Positive Returns	0.5613	0.5256	0.5206	-0.9566	0.5625	0.5528	0.5069	0.5231	-0.5300
Australia	Return Mean	0.0678	0.0265	-0.0613	-2.2800 **	0.0548	0.0047	0.0812	-0.1495	-2.0768 **
	Std. Dev. of Return	0.8039	1.1410	0.8816		0.8060	1.1794	0.8684	0.9112	
	% of Positive Returns	0.5306	0.5284	0.5018	-0.8844	0.5384	0.5096	0.5487	0.4839	-0.9993
Japan	Return Mean	0.0641	-0.0214	-0.0246	-1.7398 *	0.0643	0.0090	-0.0082	-0.0491	-1.7406 *
	Std. Dev. of Return	1.2765	1.4669	1.3049		1.2624	1.4298	1.3586	1.3836	
	% of Positive Returns	0.5380	0.4983	0.5066	-1.5900	0.5442	0.5077	0.5103	0.4902	-2.2080 **
Taiwan	Return Mean	0.2443	0.0792	0.0046	-1.3377	0.2007	0.1456	0.0433	-0.0031	-0.6810
	Std. Dev. of Return	1.2764	1.6706	1.6841	0.0000	0.4208	1.6995	1.6651	1.6798	
	% of Positive Returns	0.6923	0.5309	0.5130	-2.7795 ***	0.5000	0.5336	0.5323	0.5065	0.0185
U.S. CRSP-EW	Return Mean	0.1404	0.0472	0.0253	-5.3787 ***	0.1608	0.0926	0.0255	0.0219	-4.1985 ***
with	Std. Dev. of Return	0.8789	1.0901	1.2199		0.8335	1.0281	1.1412	1.2480	
Other Indices	% of Positive Returns	0.6028	0.5419	0.5363	-5.7902 ***	0.6342	0.5654	0.5320	0.5364	-5.2808 ***
U.S. CRSP-VW	Return Mean	0.1119	0.0403	0.0248	-3.9778 ***	0.1465	0.0742	0.0249	0.0204	-3.7618 ***
with	Std. Dev. of Return	0.9003	1.1106	1.2365		0.8443	1.0431	1.1622	1.2654	
Other Indices	% of Positive Returns	0.5777	0.5277	0.5272	-4.3666 ***	0.6203	0.5444	0.5220	0.5268	-5.0122 ***

Note:

1. $z\_score^{mean}_{k,1} = (\mu_k - \mu_1)/\sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ and $z\_score^{frequence}_{k,1} = (p_k - p_1)/\sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}$, where μ_i and σ_i are the return mean and standard deviation for bin i; p_i is the percentage of positive returns in bin i; n_i is the number of observations in bin i for each statistic.
2. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).

Table 2: Relation Between Temperature and Stock Market Returns – Overall Correlation

... continued

Panel B: Equal-Size Sample

		# of bins = 3				# of bins = 4				
		bin 1	bin 2	bin 3	z-score(3,1)	bin 1	bin 2	bin 3	bin 4	z-score(4,1)
U.S. CRSP-EW	Return Mean	0.1796	0.1180	0.0594	-2.9372 ***	0.2257	0.1326	0.0865	0.0668	-2.5777 ***
	Std. Dev. of Return	0.4845	0.5530	0.5990		0.4981	0.5006	0.6196	0.5674	
	% of Positive Returns	0.7312	0.6444	0.6406	-2.4926 **	0.7632	0.6559	0.6454	0.6356	-2.4263 **
U.S. CRSP-VW	Return Mean	0.0975	0.0749	0.0261	-1.2758	0.1222	0.1127	0.0337	0.0198	-1.1335
	Std. Dev. of Return	0.6671	0.7881	0.8039		0.7405	0.7458	0.8399	0.7517	
	% of Positive Returns	0.6022	0.5459	0.5599	-1.0655	0.6184	0.5632	0.5400	0.5624	-0.9450
Canada	Return Mean	0.0944	0.0412	-0.0205	-2.4993 **	0.1574	0.0229	0.0327	-0.0115	-2.8293 ***
	Std. Dev. of Return	0.6435	0.7156	0.6955		0.5730	0.7059	0.7297	0.6775	
	% of Positive Returns	0.5817	0.5499	0.5257	-1.6166	0.5789	0.5448	0.5478	0.5327	-0.9226
Britain	Return Mean	0.1179	0.0114	0.0341	-1.3803	0.1216	0.0555	-0.0017	0.0396	-0.8205
	Std. Dev. of Return	0.8832	0.8925	0.8719		0.8232	0.8809	0.9066	0.8551	
	% of Positive Returns	0.5201	0.5109	0.5399	0.5744	0.5100	0.5192	0.5129	0.5482	0.6387
Germany	Return Mean	0.0583	0.0301	0.0057	-0.6123	0.1442	0.0815	-0.0364	0.0035	-1.2190
	Std. Dev. of Return	1.3951	1.2525	1.1570		1.2906	1.3466	1.2123	1.0669	
	% of Positive Returns	0.5427	0.5266	0.5180	-0.7586	0.5215	0.5420	0.5183	0.5136	-0.1677
Sweden	Return Mean	0.2299	0.0852	-0.0025	-1.7096 *	0.4019	0.1531	0.0153	-0.0069	-1.8486 *
	Std. Dev. of Return	1.2819	1.3958	1.1699		1.2502	1.3888	1.3208	1.1802	
	% of Positive Returns	0.5714	0.5240	0.5331	-0.7234	0.6176	0.5551	0.5039	0.5389	-0.9106
Australia	Return Mean	0.0601	0.0071	-0.0221	-1.1299	0.0590	0.0338	-0.0009	-0.0885	-1.2442
	Std. Dev. of Return	0.7845	0.8753	0.9399		0.8258	0.8302	0.8796	0.9346	
	% of Positive Returns	0.5208	0.5222	0.5179	-0.0724	0.5329	0.5134	0.5249	0.5072	-0.3993
Japan	Return Mean	-0.0307	0.0084	-0.0681	-0.4569	-0.0067	-0.0165	0.0022	-0.1103	-0.9978
	Std. Dev. of Return	1.5144	1.4548	1.4773		1.4666	1.5548	1.3563	1.5771	
	% of Positive Returns	0.5048	0.4956	0.4845	-0.7422	0.5021	0.4993	0.5014	0.4709	-0.9193
Taiwan	Return Mean	0.3339	0.0288	-0.1178	-3.0655 ***	0.3318	0.0756	0.0498	-0.1645	-2.3359 **
	Std. Dev. of Return	2.1455	1.8891	2.0216		2.0827	2.0670	1.8224	2.0534	
	% of Positive Returns	0.5388	0.5048	0.4806	-1.6800 *	0.5688	0.5093	0.4974	0.4785	-1.7831 *
U.S. CRSP-EW	Return Mean	0.1471	0.0548	-0.0034	-4.0728 ***	0.1937	0.0900	0.0314	-0.0166	-3.8099 ***
with	Std. Dev. of Return	0.8623	1.1903	1.4883		0.7365	1.1004	1.2728	1.5667	
Other Indices	% of Positive Returns	0.5968	0.5366	0.5204	-3.8067 ***	0.6281	0.5543	0.5282	0.5171	-3.1954 ***
U.S. CRSP-VW	Return Mean	0.1346	0.0504	-0.0071	-3.7565 ***	0.1975	0.0809	0.0278	-0.0198	-3.9020 ***
with	Std. Dev. of Return	0.8829	1.2051	1.4963		0.7432	1.1171	1.2852	1.5738	
Other Indices	% of Positive Returns	0.5794	0.5256	0.5126	-3.3064 ***	0.6181	0.5382	0.5194	0.5100	-3.0951 ***

Note:

1. $z\_score_{k,1}^{mean} = (\mu_k - \mu_1) / \sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ and $z\_score_{k,1}^{frequence} = (p_k - p_1) / \sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}$, where μ_i and σ_i are the return mean and standard deviation for bin i; p_i is the percentage of positive returns in bin i; n_i is the number of observations in bin i for each statistic.
2. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).

Table 3: Relation Between Temperature and Stock Market Returns – Season Dichotomy

Panel A: Summer Season (May - September) with Equal-Size Sample

		# of bins = 3				# of bins = 4				
		bin 1	bin 2	bin 3	z-score(3,1)	bin 1	bin 2	bin 3	bin 4	z-score(4,1)
U.S. CRSP-EW	Return Mean	0.1294	0.0745	0.0476	-1.5920	0.1552	0.0649	0.0609	0.1212	-0.5135
	Std. Dev. of Return	0.3846	0.5540	0.6146		0.3903	0.5522	0.5758	0.4922	
	% of Positive Returns	0.6599	0.6465	0.6364	-0.4673	0.7051	0.6448	0.6366	0.6500	-0.7843
U.S. CRSP-VW	Return Mean	0.0452	0.0339	0.0101	-0.4699	0.1061	0.0190	0.0239	0.0268	-0.8136
	Std. Dev. of Return	0.6751	0.7691	0.7585		0.6500	0.7976	0.7643	0.6381	
	% of Positive Returns	0.5238	0.5513	0.5628	0.7413	0.5641	0.5135	0.5667	0.5500	-0.1880
Canada	Return Mean	0.0846	-0.0050	-0.0550	-2.2076 **	0.0970	-0.0338	-0.0235	0.0327	-0.8087
	Std. Dev. of Return	0.5252	0.6467	0.7473		0.5661	0.6621	0.6931	0.6161	
	% of Positive Returns	0.5816	0.5294	0.5128	-1.3376	0.5699	0.5061	0.5354	0.5455	-0.3637
Britain	Return Mean	0.0399	0.0160	-0.0118	-0.5155	0.0024	0.0006	0.0564	-0.1518	-1.0598
	Std. Dev. of Return	0.7885	0.8686	0.8864		0.7545	0.8532	0.8772	0.8682	
	% of Positive Returns	0.5252	0.5217	0.5106	-0.2435	0.5079	0.5065	0.5461	0.4516	-0.6312
Germany	Return Mean	0.0734	-0.0263	-0.0407	-0.8552	0.3458	-0.1400	0.0407	-0.0206	-2.1753 **
	Std. Dev. of Return	1.1091	1.1490	1.1279		0.8486	1.1856	1.1058	1.1799	
	% of Positive Returns	0.5446	0.5126	0.4956	-0.8207	0.5909	0.4912	0.5142	0.5345	-0.6456
Sweden	Return Mean	-0.0160	-0.0227	0.0830	0.7498	0.0559	-0.0185	-0.0147	0.0589	0.0161
	Std. Dev. of Return	1.2160	1.1813	1.1186		1.0691	1.2011	1.1922	1.0985	
	% of Positive Returns	0.4615	0.5221	0.5764	2.0411 **	0.5227	0.4918	0.5361	0.5714	0.5736
Australia	Return Mean	0.0443	0.0340	-0.1325	-1.7316 *	0.1735	0.0032	0.0267	-0.1229	-1.7834 *
	Std. Dev. of Return	0.8220	0.9181	0.9013		0.7757	0.9579	0.8311	0.9861	
	% of Positive Returns	0.5150	0.5328	0.4951	-0.3429	0.5750	0.5134	0.5316	0.5349	-0.4536
Japan	Return Mean	-0.1740	0.0392	-0.1119	0.4090	0.0242	-0.0352	-0.0121	-0.1071	-0.6035
	Std. Dev. of Return	1.2647	1.2644	1.5616		1.1981	1.2137	1.3547	1.6741	
	% of Positive Returns	0.4314	0.5204	0.4669	0.6320	0.5116	0.4950	0.4934	0.4776	-0.4051
Taiwan	Return Mean	-0.5817	-0.1466	-0.1868	1.0314	-0.5904	-0.1004	-0.1584	-0.2097	0.5040
	Std. Dev. of Return	1.8340	1.8942	2.0752		2.3723	1.6250	2.1365	1.9968	
	% of Positive Returns	0.2917	0.4790	0.4773	1.9588 **	0.4000	0.4865	0.4880	0.4626	0.4000
U.S. CRSP-EW	Return Mean	0.0187	0.0014	-0.0680	-1.7824 *	0.0594	-0.0138	0.0175	-0.1282	-2.5805 ***
with	Std. Dev. of Return	0.9843	0.9653	1.5394		0.9800	0.9845	0.9993	1.7476	
Other Indices	% of Positive Returns	0.5175	0.5333	0.5183	0.0385	0.5159	0.5176	0.5480	0.4960	-0.6376
U.S. CRSP-VW	Return Mean	0.0204	-0.0058	-0.0735	-1.9175 **	0.0558	-0.0195	0.0121	-0.1359	-2.6255 ***
with	Std. Dev. of Return	0.9897	0.9808	1.5535		0.9842	0.9952	1.0225	1.7537	
Other Indices	% of Positive Returns	0.5175	0.5195	0.5058	-0.5529	0.5127	0.5080	0.5345	0.4814	-1.0022

Note:

1. $z\_score^{mean}_{k,1} = (\mu_k - \mu_1) / \sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ and $z\_score^{frequence}_{k,1} = (p_k - p_1) / \sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}$, where μ_i and σ_i are the return mean and standard deviation for bin i; p_i is the percentage of positive returns in bin i; n_i is the number of observations in bin i for each statistic.
2. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).

Table 3: Relation Between Temperature and Stock Market Returns – Season Dichotomy

... continued

Panel B: Winter Season (October - April) with Equal-Size Sample

		# of bins = 3				# of bins = 4				
		bin 1	bin 2	bin 3	z-score(3,1)	bin 1	bin 2	bin 3	bin 4	z-score(4,1)
U.S. CRSP-EW	Return Mean	0.2051	0.1334	0.0528	-2.5816 ***	0.2517	0.1289	0.1103	0.0889	-2.1957 **
	Std. Dev. of Return	0.4739	0.5248	0.7129		0.2815	0.5080	0.5998	0.7037	
	% of Positive Returns	0.7500	0.6558	0.6171	-2.7206 ***	0.7879	0.6628	0.6384	0.6625	-1.5597
U.S. CRSP-VW	Return Mean	0.1238	0.1017	0.0069	-1.4100	0.1965	0.0666	0.0861	0.0446	-1.2961
	Std. Dev. of Return	0.6869	0.7506	0.9542		0.5082	0.7139	0.8314	0.9716	
	% of Positive Returns	0.6204	0.5613	0.5399	-1.5026	0.6970	0.5457	0.5621	0.5625	-1.5093
Canada	Return Mean	0.0994	0.0458	-0.0196	-1.6194	0.1321	0.0629	0.0154	0.0470	-0.8074
	Std. Dev. of Return	0.6435	0.7137	0.8324		0.5814	0.6437	0.7998	0.7208	
	% of Positive Returns	0.5812	0.5504	0.5327	-0.9811	0.5443	0.5532	0.5549	0.5263	-0.2245
Britain	Return Mean	0.1415	0.0442	-0.0144	-1.4835	0.0821	0.0705	0.0197	0.0421	-0.2374
	Std. Dev. of Return	0.8347	0.8868	1.0421		0.8316	0.8349	0.9805	0.8181	
	% of Positive Returns	0.5000	0.5169	0.5372	0.6565	0.4390	0.5192	0.5175	0.5690	1.2844
Germany	Return Mean	0.1461	0.0519	0.0058	-1.1263	0.1967	0.0379	0.0600	0.0499	-0.8071
	Std. Dev. of Return	1.2557	1.3492	1.2471		0.9159	1.3054	1.3766	1.3841	
	% of Positive Returns	0.5507	0.5379	0.5178	-0.6641	0.5870	0.5246	0.5453	0.5000	-1.1457
Sweden	Return Mean	0.3677	0.0980	0.0942	-1.4458	0.5166	0.1836	0.0859	0.0172	-1.7597 *
	Std. Dev. of Return	1.1310	1.4177	1.3877		1.0281	1.3925	1.4042	1.4528	
	% of Positive Returns	0.6512	0.5367	0.5189	-1.6984 *	0.7059	0.5652	0.5272	0.5130	-1.6078
Australia	Return Mean	0.0390	0.0270	-0.1164	-1.4174	0.0907	0.0298	-0.0565	-0.1249	-1.2513
	Std. Dev. of Return	0.8301	0.7294	0.7100		0.8283	0.7544	0.7712	0.6297	
	% of Positive Returns	0.5312	0.5042	0.4694	-0.8181	0.5571	0.5077	0.4859	0.4667	-0.6788
Japan	Return Mean	0.0099	-0.0715	0.1620	0.8574	-0.0034	-0.0405	-0.0411	0.3787	1.0375
	Std. Dev. of Return	1.4883	1.5253	1.8669		1.5284	1.5273	1.4122	2.5363	
	% of Positive Returns	0.5064	0.4847	0.5354	0.5914	0.5015	0.5079	0.4757	0.5400	0.5094
Taiwan	Return Mean	0.3358	0.0381	0.1865	-0.8283	0.3235	0.1670	0.0600	0.1144	-0.7378
	Std. Dev. of Return	2.1160	1.9457	1.8576		2.1611	2.0549	1.8369	1.9460	
	% of Positive Returns	0.5505	0.5006	0.5244	-0.5900	0.5679	0.5324	0.4975	0.4970	-1.0538
U.S. CRSP-EW	Return Mean	0.1290	0.0423	0.0629	-1.2730	0.2029	0.0643	0.0470	0.0455	-1.9255 *
with	Std. Dev. of Return	0.8214	1.1329	1.4386		0.7506	1.0045	1.2131	1.5683	
Other Indices	% of Positive Returns	0.6082	0.5423	0.5281	-2.9163 ***	0.6083	0.5625	0.5361	0.5202	-1.8855 *
U.S. CRSP-VW	Return Mean	0.1151	0.0304	0.0596	-1.0427	0.1962	0.0473	0.0384	0.0453	-1.8308 **
with	Std. Dev. of Return	0.8470	1.1528	1.4490		0.7576	1.0265	1.2303	1.5783	
Other Indices	% of Positive Returns	0.5836	0.5235	0.5215	-2.2384 **	0.5833	0.5379	0.5214	0.5185	-1.3729 *

Note:

1. $z\_score^{mean}_{k,1} = (\mu_k - \mu_1) / \sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ and $z\_score^{frequence}_{k,1} = (p_k - p_1) / \sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}$, where μ_i and σ_i are the return mean and standard deviation for bin i; p_i is the percentage of positive returns in bin i; n_i is the number of observations in bin i for each statistic.
2. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).

Table 4: Regressions Analysis With Monday Dummy, Tax-Dummy and Temperature

Panel A: Individual Regressions with Full Sample

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \varepsilon_t$$

	α_1	α_2	α_3	α_4	α_5	R^2
U.S. CRSP-EW	0.0863	0.3809	-0.3054	0.1798	-0.0021	0.1723
	10.7688	40.0903	-18.7260 ***	5.1848 ***	-3.0669 ***	
U.S. CRSP-VW	0.0606	0.1713	-0.1471	0.0350	-0.0016	0.0344
	5.8133	16.9216	-6.9822 ***	0.7822	-1.7319 *	
Canada	0.0375	0.1900	-0.1327	-0.0165	-0.0014	0.0394
	2.3264	15.1222	-4.8211 ***	-0.2894	-1.3369	
Britain	0.0200	0.0725	-0.1080	0.0086	-0.0051	0.0079
	0.7985	4.7544	-2.8099 ***	0.1081	-1.9127 *	
Germany	0.0223	0.0418	-0.1408	0.0575	-0.0037	0.0050
	1.1252	3.7201	-4.4329 ***	0.8647	-2.1243 **	
Sweden	-0.0425	0.0615	0.0380	0.0462	-0.0077	0.0060
	-0.9153	3.4503	0.5928	0.3409	-2.2936 **	
Australia	0.0342	0.0849	-0.0491	0.1755	0.0011	0.0089
	1.9304	5.4867	-1.2330	2.1635 **	0.2700	
Japan	0.0227	0.0039	-0.1195	-0.0906	-0.0047	0.0019
	0.9566	0.2537	-2.2788 **	-0.7475	-1.7409 *	
Taiwan	0.0896	0.1003	-0.1263	0.0075	-0.0074	0.0114
	2.9930	8.1519	-2.2780 **	0.0655	-1.9177 *	

Note:

1.For each market and regression, the first row contains the parameter estimates, and the second row contains the t-values.

2.The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test). For clarity, we only indicate the significance for explanatory variables D_t^{Mon}, D_t^{Tax}, and $Temp_t$. The last column contains R^2 of the regressions.

3.The tax dummy covers the first ten trading days of the taxation year. The tax year starts on April 6 in Britain, July1 in Australia, and January 1 in all other jurisdictions.

Table 4: Regressions Analysis With Monday Dummy, Tax-Dummy and Temperature
... continued

Panel B: SUR Test of Equal-Sized Sample with CRSP - EW

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \varepsilon_t$$

	α_1	α_2	α_3		α_4	α_5		α'_5		R^2
U.S. CRSP-EW	0.1052	0.1821	-0.2180		0.0793	-0.0019		-0.0030		0.0914
	7.7755	11.5868	-6.9750	***	1.3290	-1.7113	*	-2.3795	**	
Canada	0.0086	0.1169	-0.0296		-0.0272	-0.0017		-0.0030		0.0353
	0.4209	6.9112	-0.7475		-0.3450	-1.2564		-2.1041	**	
Britain	0.0285	0.0022	-0.0831		0.0345	-0.0024		-0.0048		0.0060
	1.0138	0.1294	-1.6321		0.4846	-0.8244		-1.4676		
Germany	0.0070	-0.0175	-0.0269		-0.1104	-0.0038		-0.0072		0.0033
	0.1908	-1.0568	-0.3749		-0.9041	-1.2001		-1.9836	**	
Sweden	-0.0141	-0.0101	-0.0477		0.0903	-0.0071		-0.0081		0.0079
	-0.3042	-0.6064	-0.6318		0.6802	-2.2073	**	-2.2252	**	
Australia	0.0278	0.0254	-0.0449		0.0412	-0.0051		-0.0043		0.0024
	1.4040	1.3576	-0.9203		0.5009	-1.2224		-0.9532		
Japan	0.0201	-0.0029	-0.2719		-0.0051	0.0009		-0.0033		0.0052
	0.5806	-0.1508	-3.2035	***	-0.0306	0.2295		-0.7821		
Taiwan	0.1478	-0.0083	-0.0122		-0.3169	-0.0276		-0.0292		0.0062
	2.3592	-0.4005	-0.1073		-1.3270	-3.4631	***	-3.6295	***	
System-wide R^2						0.0140				
$\chi2$ (8)						22.0509	^^^			
$\chi2$ (7)						15.4249	^^			

Note:

1. For each market and regression, the first row contains the parameter estimates, and the second row contains the t-values.
2. The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test). For clarity, we only indicate the significance for explanatory variables D_t^{Mon}, D_t^{Tax}, and $Temp_t$.
3. The tax dummy covers the first ten trading days of the taxation year. The taxation year starts on April 6 in Britain, July1 in Australia, and January 1 in all other jurisdictions.
4. The column with heading α_5' contains the coefficients and t-values of $Temp_t$ from individual regressions. The last column contains R^2 of the individual regressions.
5. 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 ˆ, ˆˆ, and ˆˆˆ indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 4: Regression Analysis With Monday Dummy, Tax-Dummy and Temperature

... continued

Panel C: SUR Test of Equal-Size Sample with CRSP - VW

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \varepsilon_t$$

	α_1	α_2	α_3		α_4	α_5		α'_5		R^2
U.S. CRSP-VW	0.0489	-0.0356	0.0110		-0.0978	-0.0026		-0.0040		0.0078
	2.4985	-2.1613	0.2425		-1.1120	-1.5744		-2.1995	**	
Canada	0.0100	0.0820	-0.0289		-0.0228	-0.0016		-0.0030		0.0353
	0.4904	4.9958	-0.7270		-0.2891	-1.2047		-2.1041	**	
Britain	0.0289	-0.0167	-0.0834		0.0392	-0.0024		-0.0048		0.0060
	1.0255	-0.9978	-1.6377		0.5530	-0.8300		-1.4676		
Germany	0.0073	-0.0281	-0.0264		-0.1093	-0.0038		-0.0072		0.0033
	0.1980	-1.6971	-0.3685		-0.8959	-1.1928		-1.9836	**	
Sweden	-0.0118	-0.0276	-0.0477		0.0939	-0.0069		-0.0081		0.0079
	-0.2538	-1.6352	-0.6302		0.7071	-2.1514	**	-2.2252	**	
Australia	0.0280	0.0233	-0.0451		0.0394	-0.0050		-0.0043		0.0024
	1.4125	1.2515	-0.9240		0.4797	-1.2051		-0.9532		
Japan	0.0200	-0.0050	-0.2719		-0.0040	0.0009		-0.0033		0.0052
	0.5772	-0.2615	-3.2034	***	-0.0238	0.2253		-0.7821		
Taiwan	0.1487	-0.0082	-0.0123		-0.3169	-0.0278		-0.0292		0.0062
	2.3729	-0.3991	-0.1083		-1.3272	-3.4841	***	-3.6295	***	
System-wide R^2						0.0054				
χ^2 (8)						21.8217	^^^			
χ^2 (7)						15.3690	^^			

Note:

1. For each market and regression, the first row contains the parameter estimates, and the second row contains the t-values.
2. The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test). For clarity, we only indicate the significance for explanatory variables D_t^{Mon}, D_t^{Tax}, and $Temp_t$.
3. The tax dummy covers the first ten trading days of the taxation year. The taxation year starts on April 6 in Britain, July1 in Australia, and January 1 in all other jurisdictions.
4. The column with heading α_5' contains the coefficients and t-values of $Temp_t$ from individual regressions. The last column contains R^2 of the individual regressions.
5. 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.

Table 5: Explanatory Power of Temperature, Cloud Cover, and the SAD Variable

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \alpha_6 Cloud_t + \alpha_7 SAD_t + \varepsilon_t$$

	Panel A: Cloud Cover		Panel B: Individual Test			
	Mean	Std.Dev.	$Temp_t$	$Cloud_t$	SAD_t	R^2
U. S. CRSP-EW	4.749	2.734	-0.0033	-0.0071	-0.0136	0.0969
			-2.1301 **	-1.7372 *	-1.8128 *	
U. S. 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 U.S. CRSP-EW			Panel D: SUR Test with U.S. CRSP-VW		
	$Temp_t$	$Cloud_t$	SAD_t	$Temp_t$	$Cloud_t$	SAD_t
U. S. CRSP-EW	-0.0031	-0.0035	-0.0144			
	-2.1699 **	-0.9833	-1.9742 **			
U. S. 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

Note:

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 $7.72 \cdot ar\cos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan(\lambda_t)\right]$ 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 $\lambda_t = 0.4102 \cdot \sin\left[\left(\frac{2\pi}{365}\right)(julian - 80.25)\right]$ 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, July1 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.

Table 6: Nonparametric Tests for Correlation and Temperature Level Effect

Panel A: Spearman's Rank Correlation between Temperature and Returns

	Number of Temperature Bins					
	30	40	50	60	70	100
U.S. CSRP-EW	-0.6329 ***	-0.6583 ***	-0.6268 ***	-0.5763 ***	-0.5512 ***	-0.5343 ***
U.S. CSRP-VW	-0.4679 ***	-0.3878 ***	-0.3817 ***	-0.3429 ***	-0.3201 ***	-0.2216 **
Canada	-0.4492 **	-0.3302 **	-0.2976 **	-0.2545 **	-0.2933 **	-0.2044 **
Britain	-0.2801	-0.2750 *	-0.2905 **	-0.2636 **	-0.1910	-0.1585
Germany	-0.3811 **	-0.2790 *	-0.3047 **	-0.2326 *	-0.2370 **	-0.2474 **
Sweden	-0.3366 *	-0.3771 **	-0.2547 *	-0.3138 **	-0.2698 **	-0.2012 **
Australia	-0.1417	-0.1064	-0.0805	-0.0736	-0.0781	-0.0683
Japan	-0.3531 *	-0.2949 *	-0.2887 **	-0.2442 *	-0.2932 **	-0.2019 **
Taiwan	-0.4723 ***	-0.3792 **	-0.3484 **	-0.3268 ***	-0.2876 **	-0.2602 ***
CRSP-EW & all others	-0.4616 **	-0.4443 ***	-0.4138 ***	-0.3982 ***	-0.3160 ***	-0.2950 ***
CRSP-VW & all others	-0.2627	-0.3004 *	-0.2791 **	-0.2362 *	-0.2377 **	-0.2235 **

Panel B: Chi-square Statistics for Friedman's Test

Number of Temperature Bins	CRSP-EW and all Other Indices	CRSP-VW and all Other Indices
2	5.5000 ^^	5.6667 ^^
3	6.1111 ^^	5.2222 ^
4	8.5833 ^^	9.1667 ^^
5	9.6000 ^^	7.9333 ^

Note:

1. Spearman's rank correlation is calculated based on the average temperature and return of each temperature bin. Please see the text for details. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).
2. Friedman's two-way analysis of variance is used to test the temperature level effect. The test helps to determine if investors around the globe exhibit a uniform investment behavior within the same temperature range. Please see the text for details. The carets ^, ^^, and ^^^ indicate stastistical significance of the chi-square statistics at the 10%, 5%, and 1% levels, respectively.

Table 7: Temperature Deviation Test With Equal-Size Sample

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 (k\text{-}day\ MW\ Temp\ Dev_t) + \varepsilon_t$$

	0-day MW Temp Dev $_t$	R^2	*3-day MW Temp Dev* $_t$	R^2	*7-day MW Temp Dev* $_t$	R^2	*15-day MW Temp Dev* $_t$	R^2	*31-day MW Temp Dev* $_t$	R^2
U.S. CRSP-EW	-0.00044	0.0950	-0.00041	0.0994	-0.00041	0.1035	-0.00042	0.0880	-0.00039	0.0909
	-1.88048 *		-1.76797 *		-1.75766 *		-1.89810 *		-1.76232 *	
U.S. CRSP-VW	-0.00048	0.0089	-0.00045	0.0092	-0.00046	0.0107	-0.00056	0.0083	-0.00047	0.0076
	-1.42707		-1.32952		-1.36794		-1.77095 *		-1.44533	
Canada	-0.00036	0.0295	-0.00032	0.0306	-0.00031	0.0371	-0.00032	0.0465	-0.00033	0.0407
	-1.26418		-1.13381		-1.12833		-1.24374		-1.22541	
Britain	-0.00052	0.0068	-0.00054	0.0098	-0.00054	0.0087	-0.00053	0.0059	-0.00053	0.0082
	-1.00194		-1.06361		-1.06048		-1.11128		-1.04470	
Germany	-0.00052	0.0043	-0.00052	0.0047	-0.00053	0.0049	-0.00031	0.0050	-0.00052	0.0064
	-0.82440		-0.82889		-0.84209		-0.52593		-0.84773	
Sweden	-0.00031	0.0030	-0.00044	0.0051	-0.00063	0.0065	-0.00034	0.0055	-0.00061	0.0046
	-0.48429		-0.69038		-0.99010		-0.55604		-0.97066	
Australia	-0.00002	0.0014	-0.00002	0.0014	-0.00003	0.0014	-0.00002	0.0010	-0.00002	0.0015
	-0.15059		-0.16027		-0.19735		-0.13186		-0.17065	
Japan	-0.00044	0.0057	-0.00066	0.0061	-0.00064	0.0057	0.00014	0.0064	-0.00068	0.0055
	-0.40343		-0.60249		-0.60567		0.15232		-0.65273	
Taiwan	-0.00526	0.0123	-0.00491	0.0104	-0.00470	0.0094	-0.00406	0.0102	-0.00475	0.0102
	-3.59446 ***		-3.41922 ***		-3.27036 ***		-2.97286 ***		-3.35219 ***	

Note:
1. For brevity, we only report the coefficients and the t-values for temperature deviations together with R^2 of the regressions.
2. The explanatory variable "k-$day\ MW\ Temp\ Dev_t$" ($k = 0,\ 3,\ 7,\ 15,$ and 31) is the deviation of daily temperature from a moving window average of historical daily temperatures. The moving window symetrically straddles the current day and k is the number of days used to calculate the moving average.
3. The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test) for the explanatory variable "k-$day\ MW\ Temp\ Dev_t$".
4. The tax dummy covers the first ten trading days of the taxation year. The taxation year starts on April 6 in Britain, July1 in Australia, and January 1 in all other jurisdictions.

Table 8: Regression For the Sub-Sample Periods of the U.S. CRSP index

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \varepsilon_t$$

	α_1	α_2	α_3	α_4	α_5	R^2
			CRSP Equal-weighted Index			
1962 - 1974	0.0650	0.4262	-0.3249	0.2439	-0.0009	0.2087
	4.2846	26.3470	-10.7572 ***	3.7389 ***	-0.7004	
1975 - 1987	0.0966	0.3722	-0.3453	0.1978	-0.0025	0.1706
	6.8638	23.0726	-12.1044 ***	3.2673 ***	-2.0579 **	
1988 - 1999	0.1033	0.3015	-0.2380	0.0534	-0.0036	0.1162
	8.5317	17.4744	-9.4430 ***	1.0055	-3.2776 ***	
			CRSP Value-weighted Index			
1962 - 1974	0.0596	0.2861	-0.2622	0.0632	-0.0007	0.0993
	3.7487	16.7847	-8.3144 ***	0.9310	-0.5088	
1975 - 1987	0.0797	0.1727	-0.1926	0.0958	-0.0008	0.0368
	4.0913	10.0770	-4.9176 ***	1.1518	-0.4751	
1988 - 1999	0.0483	0.0699	0.0111	-0.1347	-0.0038	0.0075
	2.6737	3.8628	0.2968	-1.7010 *	-2.3486 **	

Note:

1. For each regression, the first row contains the parameter estimates, and the second row contains the t-values. The R^2 for each regression is reported the last column.
2. The asterisks *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (two-sided test). For clarity, we only indicate the significance for explanatory variables D_t^{Mon}, D_t^{Tax}, and $Temp_t$.
3. The tax dummy covers the first ten trading days of the taxation year. The taxation year starts on April 6 in Britain, July1 in Australia, and January 1 in all other jurisdictions.

Table 9: Aggregate Bin Test and Regression Analysis for the U.S. CRSP Index

Panel A: Bin Test

		# of bins = 3				# of bins = 4				
		bin 1	bin 2	bin 3	z-score (3,1)	bin 1	bin 2	bin 3	bin 4	z-score (4,1)
CRSP-EW	Return Mean	0.2273	0.0982	0.0613	-4.7369 ***	0.2030	0.1490	0.0669	0.0579	-2.6317 ***
TEMP-EW	Std. Dev. of Return	0.5928	0.7038	0.5020		0.5779	0.5696	0.7291	0.5099	
	% of Positive Returns	0.7103	0.6289	0.6163	-3.3941 ***	0.7265	0.6432	0.6241	0.6155	-2.5704 **
CRSP-EW	Return Mean	0.2552	0.0930	0.0617	-5.6465 ***	0.2058	0.1497	0.0676	0.0570	-2.7380 ***
TEMP-PW	Std. Dev. of Return	0.5719	0.7037	0.5015		0.5806	0.5533	0.7306	0.5153	
	% of Positive Returns	0.7429	0.6229	0.6169	-4.6493 ***	0.7049	0.6515	0.6207	0.6137	-2.1061 **
CRSP-VW	Return Mean	0.1517	0.0625	0.0512	-2.0368 **	0.0884	0.1014	0.0422	0.0530	-0.4082
TEMP-EW	Std. Dev. of Return	0.8288	0.9418	0.7463		0.9138	0.7689	0.9890	0.7524	
	% of Positive Returns	0.6012	0.5433	0.5492	-1.7549 *	0.5812	0.5555	0.5468	0.5479	-0.7015
CRSP-VW	Return Mean	0.1774	0.0583	0.0512	-2.5804 ***	0.1040	0.0997	0.0383	0.0578	-0.5491
TEMP-PW	Std. Dev. of Return	0.8105	0.9373	0.7516		0.9029	0.7524	0.9895	0.7586	
	% of Positive Returns	0.6190	0.5408	0.5490	-2.3575 **	0.6066	0.5499	0.5448	0.5522	-1.1766

Panel B: Regressions

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \varepsilon_t$$

	α_1	α_2	α_3	α_4	α_5	R^2
CRSP-EW, TEMP-EW	0.1017	0.3265	-0.2911	0.1480	-0.0252	0.1375
	9.4363	22.0490	-12.7452***	3.0545***	-2.2129**	
CRSP-EW, TEMP-PW	0.1008	0.3266	-0.2911	0.1489	-0.0211	0.1375
	9.1853	22.0515	-12.7460***	3.0761***	-2.1829**	
CRSP-VW, TEMP-EW	0.0638	0.1206	-0.0757	0.0096	-0.0180	0.0162
	3.9890	7.7299	-2.2471**	0.1340	-1.0661	
CRSP-VW, TEMP-PW	0.0629	0.1206	-0.0757	0.0098	-0.0154	0.0162
	3.8695	7.7300	-2.2476**	0.1373	-1.0727	

Note:

1. This table presents bin test and regression results for the U.S. CRSP index (equal-weighted or value-weighted) and the aggregate temperature which is either equal-weighted (TEMP-EW) or population-weighted (TEMP-PW) average of temperatures in the following cities: Atlanta, Chicago, Dallas, Los Angelas, New York, Philadelphia, and Seattle. The sample period is from January 1, 1982 to December 31, 1997.
2. $z\_score_{k,1}^{mean} = (\mu_k - \mu_1)/\sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ and $z\_score_{k,1}^{frequence} = (p_k - p_1)/\sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}$, where μ_i and σ_i are the return mean and standard deviation for bin i; p_i is the percentage of positive returns in bin i; n_i is the number of observations in bin i for each statistic.
3. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test). For the regression test, we only indicate the significance for explanatory variables D_t^{Mon}, D_t^{Tax}, and $Temp_t$.
4. The tax dummy covers the first ten trading days of the taxation year which starts on January 1.

Table 10: Summary Statistics for Additional Locations

		Smaple	Daily Return (%)					Daily Temperature (Celsius)				
City, Country	Latitude	Period	# of obs.	Mean	Std. Dev.	Min	Max	# of obs.	Mean	Std. Dev.	Min	Max
Amsterdam, Netherlands	52^{0}18'N	82 - 97	4173	0.056	0.89	-11.03	7.94	5778	9.74	6.08	-11.80	25.50
Athens, Greece	37^{0}54'N	88 - 97	2607	0.082	1.76	-14.63	15.31	3604	18.01	7.11	0.60	35.00
Auckland, New Zealand	37^{0}01'S	88 - 97	2608	0.024	1.18	-12.79	9.15	3648	15.12	4.11	2.00	33.00
Buenos Aires, Argentina	34^{0}49'S	88 - 97	2605	0.418	3.78	-19.61	26.18	3536	17.00	5.99	1.70	32.65
Copenhagen, Demark	55^{0}38'N	82 - 97	4173	0.054	0.87	-8.93	6.01	5844	8.20	6.80	-17.00	25.90
Dublin, Ireland	53^{0}26'N	82 - 97	4173	0.063	1.04	-15.49	8.70	5796	9.79	4.39	-3.60	22.00
Helsinki, Finland	60^{0}19'N	87 - 97	2869	0.041	1.10	-12.54	8.74	3955	4.94	8.80	-34.25	24.85
Istanbul, Turkey	40^{0}58'N	88 - 97	2607	0.241	2.61	-12.22	13.16	3264	14.53	7.49	-4.00	29.30
Johannesburg, South Africa	26^{0}08'S	82 - 97	4173	0.067	1.24	-14.53	7.92	5467	16.19	4.33	0.45	27.00
Kuala Lumpur, Malaysia	03^{0}07'N	82 - 97	4174	0.011	1.40	-17.07	11.67	5830	27.79	1.01	21.50	33.60
Madrid, Spain	40^{0}27'N	82 - 97	4174	0.058	1.01	-9.73	6.94	5816	14.37	7.38	-3.50	31.60
Manila, Philippines	14^{0}31'N	86 - 97	3130	0.085	1.88	-15.79	15.66	4375	27.69	1.76	14.50	32.50
Milan, Italy	45^{0}26'N	82 - 97	4173	0.043	1.22	-8.44	8.40	5806	13.21	8.19	-10.05	29.60
Oslo, Norway	60^{0}12'N	82 - 97	4173	0.059	1.37	-21.09	10.32	5460	4.24	8.85	-27.95	23.50
Paris, France	49^{0}01'N	82 - 97	4173	0.053	1.01	-9.89	7.97	5387	11.27	6.58	-13.50	30.70
Rio de Janeiro, Brazil	22^{0}54'S	86 - 97	3107	0.662	3.71	-17.71	22.81	4242	21.89	2.84	11.00	33.00
Santiago, Chile	33^{0}23'S	87 - 97	2869	0.101	0.99	-12.30	6.47	3983	7.32	4.38	-6.00	22.00
Vienna, Austria	48^{0}07'N	83 - 97	3911	0.049	0.92	-9.25	7.70	5478	5.67	7.57	-22.00	23.00
Zurich, Switzerland	47^{0}23'N	82 - 97	4173	0.056	0.83	-12.31	6.62	5692	6.33	6.65	-20.20	22.00

Note:
1. Daily returns are in percentage forms. For example, the mean return for Amsterdam is 0.056%.
2. For daily temperature, due to missing observations, the number of observations across cities can be quite different even within the same sample period.

Table 11: Bin-Test for Expanded, Equal-Size Sample

		# of bins = 3				# of bins = 4				
		bin 1	bin 2	bin 3	z-score(3,1)	bin 1	bin 2	bin 3	bin 4	z-score(4,1)
New York, U.S. CRSP-EW	Return Mean	0.1268	0.0874	0.0763	-1.3275	0.1789	0.0879	0.0677	0.0912	-1.6597 *
	% of Positive Returns	0.6622	0.6339	0.6553	-0.1855	0.7115	0.6326	0.6399	0.6536	-1.1666
New York, U.S. CRSP-VW	Return Mean	0.0885	0.0540	0.0179	-1.4013	0.1373	0.0585	0.0278	0.0266	-1.5613
	% of Positive Returns	0.5856	0.5283	0.5577	-0.7208	0.6346	0.5348	0.5329	0.5599	-1.4203
Toronto, Canada	Return Mean	0.0724	0.0287	0.0259	-1.1179	0.1130	0.0424	0.0042	0.0378	-1.2844
	% of Positive Returns	0.5837	0.5350	0.5456	-1.0271	0.6231	0.5237	0.5405	0.5593	-1.3005
London, Britain	Return Mean	0.0972	0.0048	0.0876	-0.1654	0.1454	0.0235	0.0463	0.0054	-1.6132
	% of Positive Returns	0.5455	0.5006	0.5606	0.3992	0.5667	0.5167	0.5205	0.5149	-0.9395
Frankfurt, Germany	Return Mean	0.1028	0.0097	-0.0003	-1.1537	0.1612	0.0547	-0.0228	-0.0064	-1.4486
	% of Positive Returns	0.5602	0.5195	0.5180	-1.0335	0.5354	0.5409	0.5160	0.5090	-0.4505
Stockholm, Sweden	Return Mean	0.2622	0.0907	-0.0069	-1.6775 *	0.3783	0.1476	0.0191	0.0059	-1.4589
	% of Positive Returns	0.5833	0.5211	0.5314	-0.7761	0.6667	0.5342	0.5051	0.5539	-1.1285
Sydney, Australia	Return Mean	0.0752	0.0055	-0.0943	-1.8595 *	0.0816	0.0317	-0.0164	-0.0887	-1.1495
	% of Positive Returns	0.5292	0.5175	0.4700	-1.0959	0.5380	0.5105	0.5173	0.4839	-0.5797
Tokyo, Japan	Return Mean	-0.0446	0.0007	-0.0364	0.0809	-0.0025	-0.0460	0.0000	-0.0541	-0.3995
	% of Positive Returns	0.5094	0.4943	0.4751	-1.0287	0.5224	0.4876	0.4937	0.4714	-1.2409
Taipei, Taiwan	Return Mean	0.2711	0.0680	-0.1403	-2.6217 ***	0.6887	-0.0462	0.0894	-0.1767	-4.0181 ***
	% of Positive Returns	0.5571	0.5146	0.4846	-1.8574 *	0.6531	0.5013	0.5032	0.4861	-3.1695 ***
Amsterdam, Netherlands	Return Mean	0.1369	0.0330	0.0193	-1.8617 *	0.0954	0.1200	-0.0293	0.0373	-0.5389
	% of Positive Returns	0.5972	0.5414	0.5593	-0.8048	0.6250	0.5743	0.5227	0.5690	-0.7739
Athens, Greece	Return Mean	0.1137	0.1164	0.0716	-0.4001	0.1216	0.1526	0.0429	0.0737	-0.3872
	% of Positive Returns	0.5000	0.4719	0.4911	-0.2711	0.5000	0.5010	0.4758	0.4676	-0.7740
Auckland, New Zealand	Return Mean	0.1167	0.0503	-0.0525	-2.4341 **	0.1076	0.0887	-0.0074	-0.0626	-1.8219 *
	% of Positive Returns	0.5628	0.5216	0.4797	-2.0585 **	0.5505	0.5408	0.5000	0.4730	-1.3302
Buenos Aires, Argentina	Return Mean	0.3132	0.2972	0.3336	0.0829	0.1967	0.3349	0.3753	0.0320	-0.5334
	% of Positive Returns	0.5188	0.5184	0.5408	0.5742	0.5336	0.5233	0.5189	0.5192	-0.2450
Copenhagen, Demark	Return Mean	0.0720	0.0310	-0.0124	-1.4337	0.1122	0.0423	-0.0138	0.0288	-0.8483
	% of Positive Returns	0.5619	0.5319	0.5053	-1.4057	0.5373	0.5535	0.4981	0.5241	-0.1949
Dublin, Ireland	Return Mean	0.1338	0.0375	0.0220	-1.4811	0.0564	0.0919	0.0141	0.0319	-0.2198
	% of Positive Returns	0.5469	0.5076	0.4939	-1.3180	0.5055	0.5268	0.4890	0.5323	0.4252
Helsinki, Finland	Return Mean	0.1732	0.0293	0.0292	-1.2562	0.2669	0.0423	0.0091	0.0545	-1.4126
	% of Positive Returns	0.5492	0.4964	0.5046	-0.8934	0.5763	0.4991	0.4906	0.5208	-0.7935
Istanbul, Turkey	Return Mean	0.3240	0.2926	0.2805	-0.2375	0.6252	0.1414	0.3551	0.2600	-1.4567
	% of Positive Returns	0.5239	0.5222	0.5405	0.4902	0.5556	0.5151	0.5378	0.5253	-0.6812
Johannesburg, South Africa	Return Mean	0.0605	0.0194	0.1113	0.5936	0.0149	0.0027	0.0777	0.0849	0.5151
	% of Positive Returns	0.5608	0.5086	0.5656	0.1023	0.5370	0.5246	0.5206	0.5989	0.8066
Kuala Lumpur, Malaysia	Return Mean	-0.0468	0.0701	-0.0759	-0.2172	0.0262	0.0198	0.0761	-0.2846	-1.0746
	% of Positive Returns	0.4021	0.5277	0.4600	0.9011	0.3714	0.5163	0.5201	0.3846	0.1050

Table 11: Bin-Test for Expanded, Equal-Size Sample

... continued

		# of bins = 3					# of bins = 4					
		bin 1	bin 2	bin 3	z-score(3,1)		bin 1	bin 2	bin 3	bin 4	z-score(4,1)	
Madrid, Spain	Return Mean	0.0766	0.0414	-0.0584	-1.9528	*	0.0722	0.0865	-0.0497	-0.0384	-1.3048	
	% of Positive Returns	0.5303	0.4937	0.4720	-1.6408		0.5160	0.5090	0.4746	0.4915	-0.5238	
Manila, Philippines	Return Mean	0.0931	-0.0638	0.0270	-0.1707		0.1668	0.4531	-0.0157	0.0328	-0.3037	
	% of Positive Returns	0.5000	0.5000	0.4970	-0.0170		0.5714	0.6364	0.4924	0.5026	-0.3654	
Milan, Italy	Return Mean	0.1552	0.0411	-0.0511	-2.3793	**	0.2489	0.0132	0.0265	-0.0365	-2.5343	**
	% of Positive Returns	0.5521	0.5024	0.4753	-2.2202	**	0.5886	0.4979	0.4989	0.4767	-2.5045	**
Oslo, Norway	Return Mean	0.1156	0.0881	0.0339	-0.7420		0.1467	0.1365	0.0456	0.0221	-0.8029	
	% of Positive Returns	0.6040	0.5194	0.5315	-1.3781		0.6222	0.5319	0.5251	0.5260	-1.2655	
Paris, France	Return Mean	0.1691	-0.0102	-0.0325	-2.9653	***	0.2396	0.0445	-0.0404	-0.0306	-2.7641	***
	% of Positive Returns	0.5870	0.5042	0.4829	-2.7032	***	0.6619	0.5208	0.4861	0.4807	-3.3143	***
Rio de Janeiro, Brazil	Return Mean	0.7981	0.6335	0.7728	-0.0789		0.6247	0.7723	0.6212	0.7795	0.2181	
	% of Positive Returns	0.5526	0.5667	0.5679	0.3559		0.5106	0.5551	0.5841	0.5400	0.3696	
Santiago, Chile	Return Mean	0.0489	0.0889	0.0720	0.4207		0.0627	0.0795	0.0925	0.0465	-0.2434	
	% of Positive Returns	0.5000	0.5139	0.4756	-0.6546		0.5128	0.5252	0.5000	0.4588	-1.1182	
Vienna, Austria	Return Mean	0.2813	0.0326	0.0140	-2.4524	**	0.5796	0.1330	-0.0057	-0.0285	-2.6995	***
	% of Positive Returns	0.5714	0.5327	0.5052	-1.0650		0.6800	0.5683	0.5110	0.4834	-2.0342	**
Zurich, Switzerland	Return Mean	0.1880	0.0472	0.0111	-2.9456	***	0.1974	0.0991	0.0208	0.0027	-1.9647	**
	% of Positive Returns	0.6517	0.5450	0.5301	-2.9333	***	0.5974	0.5899	0.5306	0.5280	-1.1169	
U.S. CRSP-EW with Other Indices	Return Mean	0.1336	0.0717	0.0931	-1.4335		0.2233	0.1010	0.0555	0.1173	-2.0767	**
	% of Positive Returns	0.5700	0.5280	0.5175	-3.6197	***	0.6311	0.5477	0.5175	0.5175	-4.4281	***
U.S. CRSP-VW with Other Indices	Return Mean	0.1287	0.0707	0.0908	-1.3336		0.2274	0.0985	0.0545	0.1149	-2.2012	**
	% of Positive Returns	0.5644	0.5249	0.5133	-3.5118	***	0.6311	0.5428	0.5145	0.5134	-4.5891	***

Note:

1. $z\_score^{mean}_{k,1} = (\mu_k - \mu_1)/\sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ and $z\_score^{frequence}_{k,1} = (p_k - p_1)/\sqrt{\frac{p_k(1-p_k)}{n_k} + \frac{p_1(1-p_1)}{n_1}}$, where μ_i and σ_i are the return mean and standard deviation for bin i; p_i is the percentage of positive returns in bin i; n_i is the number of observations in bin i for each statistic.
2. The asterisks *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (two-sided test).
3. The common sample period is from 1988 to 1997 and the matched number of observations is 1509.

Table 12: SUR and Related Tests for Expanded, Equal-Size Sample

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \alpha_6 Cloud_t + \alpha_7 SAD_t + \varepsilon_t$$

	Panel A: Cloud Cover		Panel B: SUR with CRSP-VW			Panel C: Individual Test			
	Mean	Std. Dev.	$Temp_t$	$Cloud_t$	SAD_t	$Temp_t$	$Cloud_t$	SAD_t	R^2
New York, U.S. CRSP-VW	4.749	2.734	-0.0015	-0.0016	0.0331	-0.0024	-0.0080	0.0148	0.0108
			-0.6120	-0.2063	0.5286	-0.9344	-0.9415	0.2312	
London, Britain	5.832	1.889	-0.0021	0.0049	0.0391	-0.0034	-0.0094	0.0267	0.0085
			-0.4810	0.4714	0.5183	-0.6311	-0.6591	0.3360	
Stockholm, Sweden	5.309	1.955	-0.0026	-0.0028	0.0750	-0.0069	-0.0019	-0.0015	0.0073
			-0.5021	-0.1662	0.6667	-1.1014	-0.0848	-0.0118	
Sydney, Australia	3.812	2.320	-0.0219	-0.0084	-0.1465	-0.0279	-0.0035	-0.2435	0.0137
			-3.1561 ***	-0.9234	-1.6381	-3.0909 ***	-0.2947	-2.2378 **	
Taipei, Taiwan	5.432	1.918	-0.0429	0.0005	0.0863	-0.0439	0.0092	0.0909	0.0151
			-3.0882 ***	0.0124	0.4518	-3.0859 ***	0.2387	0.4692	
Amsterdam, Netherlands	5.434	2.239	-0.0086	0.0024	-0.1025	-0.0136	-0.0104	-0.1570	0.0120
			-2.4431 **	0.3593	-1.5935	-2.8576 ***	-0.9146	-2.1878 **	
Athens, Greece	3.431	2.592	-0.0029	-0.0339	-0.2388	-0.0075	-0.0417	-0.2754	0.0233
			-0.3026	-1.4059	-1.3328	-0.7511	-1.6463 *	-1.5059	
Auckland, New Zealand	4.685	2.272	-0.0286	0.0085	-0.1468	-0.0352	0.0157	-0.2907	0.0142
			-2.7955 ***	0.6818	-1.1892	-2.7920 ***	1.0070	-2.0269 **	
Buenos Aires, Argentina	4.152	2.774	-0.0147	0.1112	-0.1977	-0.0077	0.1093	-0.1122	0.0231
			-0.5650	2.3893 **	-0.4401	-0.2909	2.2956 **	-0.2454	
Copenhagen, Demark	5.362	2.199	0.0014	0.0189	0.1266	-0.0017	0.0240	0.0836	0.0244
			0.3446	1.8282 *	1.8034 *	-0.3635	1.9171 *	1.0762	
Dublin, Ireland	5.904	1.829	-0.0070	-0.0033	-0.0119	-0.0119	-0.0148	-0.0437	0.0126
			-1.0716	-0.2430	-0.1460	-1.5559	-0.8954	-0.4918	
Helsinki, Finland	5.533	2.330	-0.0026	-0.0104	0.1450	-0.0046	-0.0162	0.1138	0.0317
			-0.5868	-0.7846	1.4812	-0.9374	-1.0501	1.0837	
Istanbul, Turkey	3.921	2.576	0.0011	-0.0086	0.0332	-0.0014	-0.0052	0.0092	0.0201
			0.0924	-0.2736	0.1465	-0.1237	-0.1599	0.0401	
Johannesburg, South Africa	3.061	2.420	-0.0022	-0.0124	-0.2245	-0.0060	-0.0010	-0.3176	0.0194
			-0.2571	-0.9386	-1.9471 *	-0.6185	-0.0650	-2.5351 **	
Kuala Lumpur, Malaysia	6.866	0.352	-0.0066	0.0684	0.0437	0.0103	0.0825	0.0236	0.0190
			-0.1704	0.7752	0.4049	0.2349	0.8202	0.2040	

Table 12: SUR and Related Tests for Expanded, Equal-Size Sample

... continued

$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 Temp_t + \alpha_6 Cloud_t + \alpha_7 SAD_t + \varepsilon_t$

	Panel A: Cloud Cover		Panel B: SUR with CRSP-VW			Panel C: Individual Test			
	Mean	Std. Dev.	$Temp_t$	$Cloud_t$	SAD_t	$Temp_t$	$Cloud_t$	SAD_t	R^2
Madrid, Spain	3.597	2.621	-0.0023	0.0188	0.0938	-0.0058	0.0213	0.0444	0.0116
			-0.6054	2.0446 **	1.1016	-1.1929	1.6365	0.4677	
Manila, Philippines	5.312	2.055	-0.0043	0.0149	-0.0061	-0.0140	0.0072	-0.0239	0.0465
			-0.1575	0.6418	-0.0436	-0.4873	0.2960	-0.1649	
Milan, Italy	4.102	2.792	-0.0032	0.0128	0.0573	-0.0058	0.0235	0.0166	0.0231
			-0.6560	1.1162	0.5342	-1.0670	1.7209 *	0.1452	
Oslo, Norway	5.439	2.256	-0.0035	-0.0033	-0.1348	-0.0063	0.0137	-0.1928	0.0178
			-0.6937	-0.2151	-1.1523	-1.0545	0.7098	-1.5059	
Paris, France	5.294	2.298	-0.0073	-0.0097	-0.0032	-0.0133	-0.0261	-0.0581	0.0141
			-1.8226 *	-1.1849	-0.0390	-2.5643 **	-2.0224 **	-0.6641	
Santiago, Chile	3.099	3.065	-0.0029	0.0049	-0.1974	-0.0019	0.0042	-0.2099	0.0863
			-0.4460	0.6366	-2.2846 **	-0.2754	0.5327	-2.3655 **	
Vienna, Austria	5.076	2.459	-0.0023	-0.0137	0.0345	-0.0084	-0.0094	-0.0448	0.0600
			-0.5084	-1.2007	0.3723	-1.6223	-0.6803	-0.4473	
Zurich, Switzerland	5.283	2.465	-0.0052	-0.0077	0.0145	-0.0098	-0.0088	-0.0326	0.0116
			-1.5076	-1.1072	0.2034	-2.1207 **	-0.7984	-0.4141	
System-wide R^2					0.0251				
$\chi^2(23)$			35.8773 ^^	25.3794	31.7398				
$\chi^2(22)$			33.5255 ^	32.8806 ^	30.2556				

Note:

1. This table is a counterpart of Table 5 with an expanded, equal-size sample. See Table 5 for notes. The equal-size sample is from 1989 to 1997, and the matched number of observations is 1013.
2. The taxation year starts on April 6 in Britain and Ireland, July 1 in Australia, April 1 in New Zealand, March 1 in South Africa, and January 1 in all other jurisdictions.

Figure 1: Historical Daily Average Temperature

Figure 2: Moving Average of Historical Daily Average Temperatures for New York

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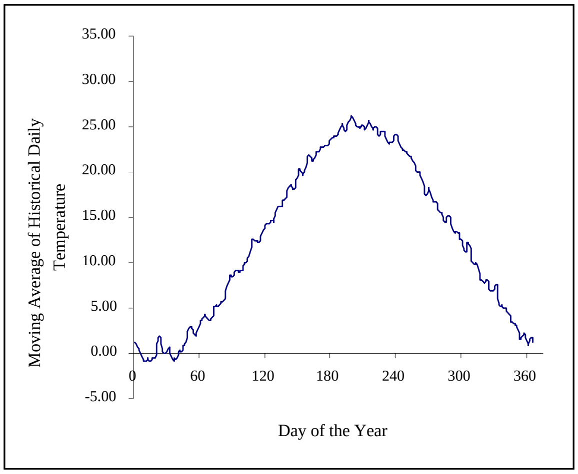
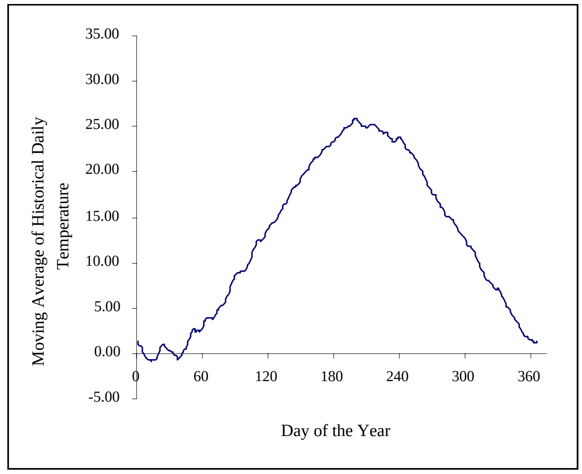
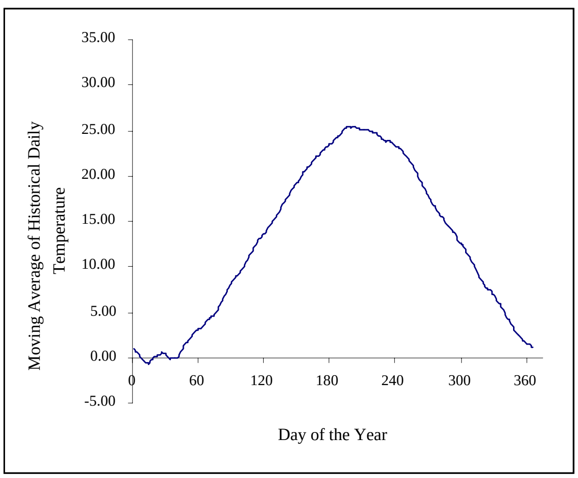
Panel A: 3-day Moving Average



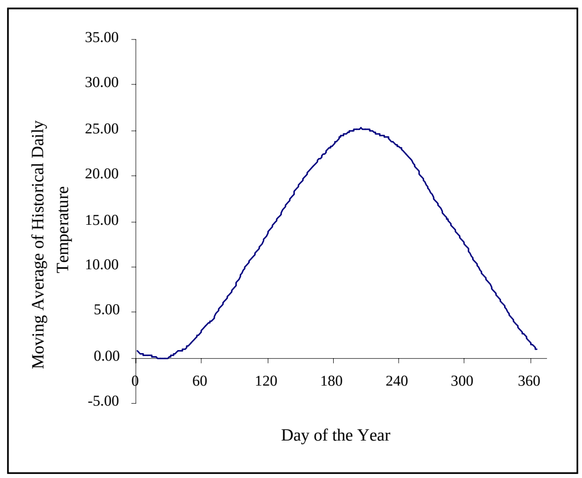
Panel B: 7-day Moving Average



Panel C: 15-day Moving Average



Panel D: 31-day Moving Average



Note: The plots are for the moving average of the historical daily average temperatures presented in Figure 1. The moving window symmetrically straddles the current day. For example, in the case of a 3-day moving window, we use the temperatures for the previous day, the current day and the next day to calculate the moving average.

To obtain the moving average for days at the beginning and end of the year, we simply stack the historical daily average temperatures. To continue the above example, the moving average for January 1 is calculated using the historical daily average temperatures for December 31, January 1 and January 2.