Stock Market Returns: A Temperature Anomaly *

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First draft: November 2001
Current Draft: August 2002

Abstract

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Keywords*: stock market returns, stock market anomalies, temperature anomaly, HDD, CDD.*

JEL classifications: G14, G10, G15.

* Both authors are grateful to the Social Sciences and Humanities Research Council of Canada for financial support. They thank Kevin Zhu for his excellent research assistance. They would also like to thank Ming Dong, Mark Kamstra, and Lisa Kramer for helpful discussions and comments.

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Abstract

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1. Introduction

Identifying the links between meteorological variables and human behavior has long been a scientific endeavour (e.g. Wyndham, 1969; Bell and Baron, 1976; Moos, 1976; Allen and Fisher, 1978; Cunningham, 1979; Schneider, Lesko and Garrett, 1980; Bell, 1981; and Sanders and Bizzolara, 1982). As succinctly summarized by Howarth and Hoffman (1984), researchers hypothesize that weather affects mood which in turn regulates behavior. The typical weather variables under study include 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 impact on mood. In particular, the three variables in order of importance had significant effects on concentration. In addition, under extremely cold temperatures, say between -8°C and -28°C, people reported increased aggressive feelings. Some studies have examined the impact of ambient temperature alone on mood, behavior and task performing. Allen and Fisher (1978), and Wyndham (1969) both found that task performing abilities go down when subjects are under very high or low temperature. Wyndham (1969) found behavioral changes in the form of hysteria and apathy under extreme heat. Meantime, Cunningham (1979), and Schneider, Lesko and Garrett (1980) found that people tend to be less willing to extend help to others when under hot or cold temperatures. On the predisposition of aggression, researchers (e.g. Baron and Ransberger, 1978; Palamerek and Rule, 1980; Bell, 1981; and Howarth and Hoffman, 1984) have obtained evidence that suggests increased level of aggression under high ambient temperature. By the same token, Schneider, Lesko and Garrett (1980) inferred that cold temperature can also lead to aggression due to its sheer discomfort. On balance, it appears that extreme temperatures, either very high or very low, tend to cause aggression; and that high temperatures can also cause hysteria and apathy.

As behavioral finance takes its roots in mainstream financial research, a burgeoning sub-field has emerged which inquires about how meteorological conditions affect investors' behavior and hence 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.[1] If meteorological conditions affect mood, then they will influence investors' risk aversion and risk assessments, which in turn affect their investment behavior.

Focusing on New York city, Saunders (1993) demonstrated a convincing 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: DJIA, NYSE/AMEX value-weighted, and NYSE/AMEX equal-weighted. He found that less cloud cover is associated with higher returns, and the return difference between the two end bins (i.e. the most cloud cover and 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 on sunny days, which produces a lift to the stock markets, and that the negative mood on cloudy days depress the stock returns. The above findings and inferences were confirmed by Hirshleifer and Shumway (2001) who rigorously examined 26 stock market indices around the globe for the period of 1982 - 1997. For most of the indices, a strong positive correlation is found between the amount of sunshine and daily returns.

Kamstra, Kramer and Levi (2000), by examining stock markets in the United States, Canada, the United Kingdom, and Germnay, found that for the weekend which coincides with the daylight savings time change, the stock market returns are substantially lower than returns on other weekends. Based on desynchronosis literature, they postulated that the disruption of sleep pattern around the time change would impair judgment and raise anxiety, which in turn cause investors

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

to seek for safety and avoid risk-taking, the end result of which is to depress the stock prices. In a subsequent study, Kamstra, Kramer and Levi (2002) 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 thanks to the SAD effect or "winter blues". This hypothesized relationship was confirmed for a dozen or so international markets.

Finally, two groups of authors (Dichev and Janes, 2001; and Yuan, Zheng and Zhu, 2001) independently documented linkage 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 around a new moon.

In this paper, we examine the potential linkage between temperature and stock market returns. The above reviewed psychological literature reveals that temperature is one of the three important weather variables affecting people's mood, and that high or low temperatures tend to mediate mood, which in turn affects behavior. Just as the amount of sunshine or the length of the night affect investors' behavior through mood and psychological state, we expect a similar linkage between temperature and market returns. Therefore our research complements the aforementioned inquiries. Similar to Saunders (1993), and Hirshleifer and Shumway (2001), we relate a stochastic variable, i.e., daily temperature, to stock returns. In contrast, Dichev and Janes (2001), Kamstra, Kramer and Levi (2002), and Yuan, Zheng and Zhu (2001) relate deterministic cyclical variables to stock returns. Given the psychological evidence, we hypothesize that lower temperatures are associated with higher stock market returns due to aggressive risk taking, and higher temperatures can lead to higher or lower stock returns since both aggression (associated with risk-taking) and apathy (associated with risk-avoidance) are possible behavioral consequences and the net impact on investors' risk taking depends on the trade-off between the two.

We would like to issue two caveats at this point. First, although psychological studies have been conducted under both room / ambient temperature and outdoor temperature, in today's society, most dwellings and office buildings are equipped with cooling and heating devices so that the indoor temperature is within comfort range, however that is defined in each situation. 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 hence impact their behavior. In this sense, the temperature impacts on investors' behaviour are exerted in the same way the amount of sunshine exerts its impact (Hirshleifer and Shumway, 2001), since traders work indoors and in many cases, in windowless trading rooms. Second, to our knowledge, there is no psychological literature that directly inquires 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, as mentioned by Hirshleifer and Shumway (2001), mood-induced return patterns directly contradict rational thinking and market efficiency. For this reason, we will call the potential linkage between temperature and stock returns an "anomaly", in much the same way as we dub the small-firm effect or day-of-the-week effect.

Our analysis does indeed reveal a temperature anomaly. We find that the stock returns tend to be negatively correlated with the temperature: the lower the temperature the higher the returns, and vice versa. This relationship is much stronger and statistically significant when the temperature is low and when the city which houses the stock exchange sees a bigger temperature variation. Our hypothesis that lower temperatures are related to higher stock returns is confirmed. When the temperature is high, apathy seems to dominate aggression in risk taking, resulting in an overall lower stock return. But this relationship is not statistically significant, mostly due to the trade-off between the two competing effects. We also show that the relationships are robust to various alternative tests and specifications, and are stable over time. In addition, the relationship still remains true after taking into account the geographical dispersion of investors relative to the city where the stock exchange resides.

The rest of the paper is organized as follows. Section 2 presents the data and discusses summary statistics. Section 3 reports the empirical linkage between temperatures and stock returns while controlling for various known anomalies. Section 4 presents auxiliary analyses and examines the robustness of our results to various alternative specifications. Section 5 provides a brief summary and some concluding remarks. Tables and figures are collected at the end of the paper.

2. Data

Our empirical investigation is conducted 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 tempterature data are purchased from the Earth Satellite Corporation (EarthSat).[2] 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 globle.

Table 1 presents the stock exchanges, city locations, weather stations, and summary statistics. 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 which have the largest volume of trading measured in Swedish kronor on the Stockholmsbörsen. Using value-weighted indices

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

allows us to avoid the potential dominance of small-cap stocks in detecting investors' reaction to temperature changes. Nonetheless, by considering both the equal- and the value-weighted indices for the U.S., we are able to uncover the potential difference in temperature effects with the two weighting schemes.

For the temperature, 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 the same sample period, we always have more observations for temperatures than for returns since returns can only be observed for trading days. For eventual analyses, we eliminate temperature observations for holidays and weekends so that the two series are perfectly matched. After matching, Sweden has the smallest sample size of 3129 while the U.S. has the largest sample size of 9442.

The mean ranges from 6.97°C in Stockholm, Sweden to 22.81°C in Taipei, Taiwan. The standard deviation of the 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 likely or often to have extremely cold days than extremely hot days.

To illustrate the temperature fluctuations throughout the calendar year, we plot in Figure 1 the historical average daily temperature for four cities: New York, London, Sydney and Tokyo.[3] For cities on the Northern Hemisphere, the progression of temperature follows similar patterns throughout the year, although the range of variations can be quite different. Naturally, an antithetic 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 in our sample. This will have some implications for temperature impact on investment behavior. Specifically,

[3] "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.

investors there may not react very strongly to temperature changes when the changes themselves are not dramatic, as borne out by our analyses to be presented below.

For daily returns, the mean ranges from 0.005% for Nikkei 225 to 0.075% for the equal-weighted NYSE index. The standard deviation varies across indices, with Taiwan Weighted being the most volatile at 1.67% and TSE300 the least volatile at 0.37%. 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 strong kurtosis.

3. Methodology and Empirical Results

Based on the discussions in the introduction, our formal hypothesis can be stated as: *lower temperatures are associated with higher stock market returns, and higher temperatures can be associated with either higher or lower stock returns.* To formalize the definition of "comfortable temperature" versus high or low temperature, we follow the utility industry's convention and transform the daily average temperature to either heating-degree-days (HDDs) or cooling-degree-days (CDDs). The comfortable temperature is set at 65 degrees Fahrenheit, or 18.33°C. HDDs occur when the daily temperature is below 18.33°C while CDDs occur when the daily temperature is above 18.33°C. They indicate the extent to which the room has to be heated or cooled. The precise expressions of HDDs and CDDs are given below:

$$\begin{aligned}
\text{Daily HDDs} &= \max\left[18.33 - \text{daily temperature}, 0\right], \\
\text{Daily CDDs} &= \max\left[\text{daily temperature} - 18.33, 0\right].
\end{aligned}$$

A particular day will register either HDDs or CDDs, but not both. In other words, the HDD / CDD measure for a particular day is either a positive number or zero. Consequently, corresponding to each stock return series, we have two series of temperature observations, one for HDDs and one for CDDs.

We will implement two methodologies to test the hypothesis. First, following Saunders (1993), we group returns according to certain temperature ordering to detect potential associations. We will call this the "bin test". Second, similar to Hirshleifer and Shumway (2001), and Kamstra, Kramer and Levi (2002), we perform regression tests to quantify the precise linkage after controlling for other known anomalies such as Monday effect and tax-loss selling effect.

3.1. The Bin Tests — Uncovering Correlation between Temperature and Returns

Given our purpose of uncovering the linkage between the temperature and stock market returns, we will first relate the HDDs and CDDs to stock returns. Since the testing procedures are exactly the same for HDDs and CDDs, in the following expositions, we will only speak of HDDs for brevity. Our objective is to identify potential correlations between HDDs and the stock market returns. To this end, for each stock market location, we first sort the matched data by HDDs in ascending order, and then divide the HDDs into sub-groups or bins. For each HDD bin, we calculate the mean return and the frequency or percentage of positive returns for days belonging to that bin. We then compare the mean returns associated with the smallest HDD bin and the largest HDD bin, and test whether the difference in mean returns is significant. Similar comparison and test are also done for the percentage of positive returns in each bin. If, for example, lower temperatures are indeed associated with higher stock returns, then we would expect that the higher returns are broadly based rather than being driven by a few extreme outliers. In other words, we expect the percentage of positive returns to be high in this case.

The precise testing procedure is as follows. First, we compute the difference between the maximum and minimum of the HDD series. The minimum is zero if we do not exclude days when the daily temperature is above 18.33°C. Then, we divide the difference by the number of bins, k to obtain the HDD range of each bin. That is,

$$\Delta = \frac{HDD_{\max} - HDD_{\min}}{k}.$$

The first bin contains HDDs falling into the range $[HDD_{\min}, \Delta)$; the second bin contains HDDs in the range $[\Delta, 2\Delta)$; ... and so on. For example, if the maximum and minimum HDDs are 12 and 0, respectively, and the number of bins is 3, then the first bin will contain HDDs ranging from 0 to 4, the second bin ranging from 4 to 8, and the third ranging from 8 to 12.

To determine whether the mean returns associated with the largest HDD bin (i.e. bin k) and the smallest HDD bin (i.e. bin 1) are significantly different, we follow Saunders (1993) and compute the following z statistic:

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

where μ_i, σ_i^2 and n_i stand for the mean return, the variance of returns 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:

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

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

Similar to the reasoning of Saunders (1993), we argue that 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 HDDs, 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). But in our study, all return variances for the bins in each test are almost identical, as shown in Table 2. Stock return variances may change as a function of time, but not as a function of temperature.

The above calculations and tests are done for all market indices with 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 2-bin and 3-bin cases. Table 2 contains the HDD results, and Table 3 contains the CDD results.

Table 2 shows a striking correlation between returns and HDDs. For all stock markets, the higher the HDDs (or the lower the temperature), the higher the average returns; and this relationship is strictly monotonic. Other than Australia and Taiwan (2-bin case), the z statistics for all markets are significant at the 10% level, with many being significant at the 1% level. Equally striking, similar associations and statistical significance are observed with the frequency of positive returns. The lower the temperature, the more likely that stocks will experience a positive price change.

For Australia, though the z statistics are not significant, the ranking of mean returns and frequency of positive returns is consistent with that for other markets. This is an important observation in that the winter seasons on the Northern and Southern Hemispheres actually cover different calendar months. To further the point, we plot in Figure 2 historical average HDDs for each of the calendar days for four locations. It is seen that, for much of the time when HDDs are positive for locations on the Northern Hemisphere, the HDDs are zero for Sydney, and vice versa. This implies convincingly that there is a common drive to the stock market returns by temperature. The insignificance of the z statistics may be due to the narrow range of temperature variations in Australia, as evidenced in Table 1 and Figure 1.

One concern with the above analysis is the inclusion of zero HDDs in all calculations. For all stock exchange locations, while there are sporadic observations of zero HDDs during the winter season, most of the zero HDDs occur in the summer season. By construction, stock returns in the summer are included in the smallest HDD bin. If stock returns are on average lower in the summer, then our results may be biased in favour of the patterns observed. To investigate this potential bias, we repeat the analysis in Table 2 by eliminating observations involving zero HDDs. The results are almost the same as the full sample case, and we omit the table for brevity (but available upon request). The magnitude of returns for the smallest HDD bin did not change much. Interestingly, for Australia, the z statistics improve slightly and those for the percentage of positive returns are now significant at the 10% level.

We now turn to CDD results. Table 3 is a CDD counterpart for Table 2. To begin with, when we divide the observations into three bins, there are no clear pattern emerging from all markets. But with only two bins, except for Canada, we see a clear negative correlation between average returns and CDDs. With a minor exception of Taiwan, the percentage of positive returns are all lower when CDDs are higher. The z statistics are either insignificant or only significant at 10% level. The results are similar when observations involving zero CDDs are excluded. Overall, Table 3 reveals that stock market returns tend to be lower when the temperature is high, and that this relation is not as strong as that when the temperature is low. Interestingly, the results in Tables 2 and 3 together seem to indicate a general relation: the lower the temperature the higher the returns, and the higher the temperature the lower the returns.

Finally, for both the HDD and CDD cases, we observe that the temperature impact is much stronger on the equal-weighted CRSP 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 broad based large-cap stocks.

To this point, we have basically confirmed our hypothesis that lower temperatures are associated with higher returns. As for higher temperatures, we find that they are associated with lower returns.

Apparently, apathy dominates aggression in risk taking in this case. Next, through regression analysis, we will control for some of the known anomalies in stock returns and uncover the precise sensitivity of returns to temperature changes.

3.2. The Regression Analysis — Controlling for Known Anomalies

Similar to Kamstra, Kramer and Levi (2002), we correct for first-order auto-correlation in returns, the Monday effect and the tax-loss effect. We will also implement two versions of the regression analysis: two-pass regressions and a single-pass regression. To run the two-pass regressions, we first obtain the residual from the following regression

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

where r_t is daily index 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; and ε_t is the residual term. The tax year starts on April 6 in Britain, July 1 in Australia and January 1 for all other jurisdictions.

The second pass involves regressing the residuals from (3.1) on HDDs and CDDs. That is

$$\widehat{\varepsilon}_t = \beta_1 + \beta_2 HDD_t + \beta_3 CDD_t + \eta_t \tag{3.2}$$

where η_t is a disturbance term. If the coefficient estimates for the HDD and CDD variables are significant, then the temperature impact on returns is an anomaly in its own rights, after removing the documented Monday effect and tax-loss effect.[4]

Table 4 presents the two-pass regression results. As shown in Panel A, except for Sweden, returns on Mondays are lower for all markets. This Monday effect is significant at the 5% level except for Australia. In contrast, the tax loss effect is significant for only the U.S., German, and

[4]For all regressions, we standardize the HDD and CDD variables by dividing the reference temperature 18.33°C into the original values of the HDD and CDD. This only re-scales the coefficients, but does not affect the t-values.

Australian markets. Nonetheless, with the exception of Japan, all markets exhibit the right sign for the tax-loss effect.

Panel B reports the second pass regression results. It is seen that the strong positive correlation between returns and HDDs remain even after controlling for auto-correlations, the Monday effect and the tax-loss effect. The HDD coefficient estimates for Australia and Taiwan are not significant although they are with the right sign. For other markets, the HDD coefficient is significant at the 5% level or higher. As for the CDD coefficient, it is insignificant for all markets, and it retains the right sign for only Britain, Germany and Taiwan. Overall, the results in Panel B implies that the temperature impact is much more pronounced when the temperature is low than when it is high. It should be noted that the temperature impact is indeed of economic significance. For instance, for the CRSP value-weighted index, the HDD coefficient is 0.046%, which is almost as big as the daily mean return itself as shown in Table 1. It means that if, for example, the temperature is 10 degrees lower than average, then we can expect the return to be 0.025% (= 0.046% × 10 / 18.33) higher for that day alone. This return increment is about half of the average daily return itself!

To see if the temperature variables have the same competing power as the control variables in the first-pass regression, we do a one-pass regression by including all variables in one equation:

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t + \alpha_6 CDD_t + \varepsilon_t \tag{3.3}$$

The results for this estimation is shown in Table 5. With several minor changes, e.g., the coefficient for the tax-loss dummy becomes negative for Canada, all results remain virtually the same. In fact, we see a slight improvement for almost all t-values for the HDD and CDD variables.

At this point, 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 (2001) both found that stock market returns are positively related to the amount of sunshine or negatively related to the extent of cloud cover. Kamstra, Kramer and Levi (2002) 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 through the fall and winter. In general, longer nights are found to be related to lower stock returns.

To control for the above anomalies, ideally we would like to run a multivariate regression as in (3.3) with two additional independent variables: cloud cover and SAD_t, the latter being the number of hours of night minus 12 for the period of September 21 to March 20, and zero otherwise. However, HDD_t and SAD_t can be correlated since colder days tend to be longer-night days in the winter. To avoid the complication of multicolinearity, we run a two-pass regression. In the first pass regression, we control for the Monday effect, the tax loss effect, the cloud cover effect and the SAD effect:

$$r_t = \gamma_1 + \gamma_2 r_{t-1} + \gamma_3 D_t^{Mon} + \gamma_4 D_t^{Tax} + \gamma_5 Cloud_t + \gamma_6 SAD_t + \epsilon_t; \tag{3.4}$$

where $Cloud_t$ measures the cloud cover, and SAD_t meaures the length of the night, the precise calculation of which is given in Table 6. In the second pass, we regress the residual from (3.4) on HDD_t and CDD_t as follows:

$$\widehat{\epsilon}_t = \varphi_1 + \varphi_2 HDD_t + \varphi_3 CDD_t + \xi_t. \tag{3.5}$$

We then examine the t-values of the estimated coefficients in order to compare the explanatory power of the competing variables. If γ_5 and γ_6 are estimated with significant t-values but φ_2 and φ_3 are not, then we can infer that, after controling for the cloud cover effect and the SAD effect, temperature does not have additional explanatory power. However, if φ_2 and φ_3 are estimated with significant t-values, then we know that temperature is related to stock returns even after controlling for the two nature-related anomalies. To facilitate discussions, we also run (3.3) for the reduced sample which is delineated below.

As in Hirshleifer and Shumway (2001), our cloud cover data are obtained from the National Climatic Data Center, and we also use the "total sky cover" to measure cloud cover, denoted by $Cloud_t$, which is 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.[5] Since the cloud cover data are only available for the period of 1982 to 1997, and our merged data of temperature and stock market returns cover unequal periods as shown in Table 1, merging all data results in different lengths of sample period for the remaining markets. Table 6 reports, for each market, the number of observations, the mean and standard deviation of cloud cover, and the regression results. Several observations are in order.

First, the t-values of the coefficient estimates for HDD_t and CDD_t in regression (3.3) are generally lower than their counterparts in Table 5, which is a result of smaller samples. Nonetheless, the statistical significance is almost the same. For the HDD_t variable, other than Australia and Taiwan, all coefficients are significant at the 10% level, and many are significant at the 5% level.

Second, for the cloud cover variable, the coefficient estimate is negative for all markets other than Taiwan, and it is only significant for Australia (at the 5% level). This confirms the hypothesis and findings of Hirshleifer and Shumway (2001), namely, higher stock returns are related to sunny days. Hirshleifer and Shumway (2001) also found that the regression coefficient tends to be negative for most cities, but is rarely significant. Interestingly, as shown in Panel A of Table 6, Sydney has the lowest sample average of cloud cover, i.e., it is the "sunnies" city. Apparently, the amount of sunshine has a significant impact on the stock market returns in this sunshine state. As for the length-of-the-night variable, SAD_t, the coefficient estimate is negative only for the U.S. (CRSP-equally weighted), Sweden, and Australia. None of the t-values is significant. By and large, our

[5]Hirshleifer and Shumway (2001) had similar exlusions in the their study.

samples confirm that higher cloud cover is related to lower stock returns, and for some markets, longer nights are associated with lower returns.

Third, by comparing the t-values for HDD_t and CDD_t in regression (3.3) and regression (3.5), we see that with the exception of Australia, for all markets, the temperature variables essentially retain their explanatory power after controlling for the cloud cover effect and the SAD effect. The results convincingly show that 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 observations in this section indicate that the relationship between temperatures and stock market returns is statistically significant even after controlling for 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 impact of temperature on stock returns is also economically significant, and a trading strategy can be easily implemented to exploit this anomaly. For example, in the winter season, an investor could long the index when it is very cold and short it when it is mild.[6] As discussed before, a 10-degree deviation in temperature could mean an average daily return difference of 0.025% for the CRSP value-weighted index, which is half of the average daily return itself. Assuming 250 trading days in a year, a 10-degree deviation in temperature means a return difference of 6.25% on an annual basis.

4. Auxiliary Analyses

4.1. Alternative definitions of HDDs and CDDs

Throughout the analysis we have been following the convention to define HDDs and CDDs using 18.33°C as the reference temperature. For many countries and locations, 18.33°C is not necessarily the average temperature or "comfortable temperature". An alternative specification for the

[6] Most of the major market indices have corresponding exchange traded funds (or ETF's) which can be bought or sold just like individual stocks.

benchmark temperature which is free of location bias would be the sample average temperature as reported in Panel B of Table 1. We repeat all the analyses by re-defining HDDs and CDDs using the sample average as the reference temperature. It turns out that all results remain almost the same. For brevity, we only report two sets of results. Table 7 is a counterpart of Table 2 with the alternative definition for HDDs, and Table 8 is a counterpart of Table 5 with the alternative definitions for HDDs and CDDs. It is seen that with some very minor variations, the results remain the same both quantitatively and qualitatively.

4.2. Bin test using HDD deviations

The bin tests involving HDDs show a very strong positive relation between returns and realized HDDs. It is of interest to see if a similar relation exists between returns and deviations of realized HDDs from historical average HDDs, the latter of which are simply HDDs based on sample historical average temperatures. A positive deviation means a colder-than-normal day and a negative deviation means the opposite. Insofar as HDDs may capture the overall seasonal impacts of temperature on returns, the HDD deviations can capture the impact of daily temperature shocks.

To carry out the investigations, we first calculate the HDD deviations, and divide them into positive and negative groups. Then for each group, we construct the bin tests as before. It turns out that there is no clear-cut one-way relation between returns and negative deviations, but that there is still a strong positive relation between returns and positive deviations. We report in Table 9 the results for positive HDD deviations. It is seen that except for indices in Canada, Australia and Japan, the positive relation between returns and positive HDD deviations is significant for all indices. We can therefore infer that the overall positive relation between returns and HDDs is mostly driven by below average temperature realizations.

More importantly, the above results do confirm that the relationship between the temperature and the stock market returns is a manifestation of the day-to-day impacts of temperature shocks, as opposed to a reflection of a general seasonal effect. Subtracting the historical average HDDs from the realized HDDs 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 the amount 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.

4.3. Alternative regression speficiations

We repeat the two-pass regressions by using either HDDs or CDDs alone in the second pass. The magnitude and significance for the HDD coefficient remain more or less the same. But the sign for the CDD coefficient is now more consistent with the 2-bin results in Table 3. This confirms the observation that there is indeed a negative correlation, albeit a weak one, between returns and CDDs. We also repeat all regressions using a 5-day or one-month window for the tax-loss dummy. All results remain similar. To conserve space, we omit the tables.

4.4. Inter-market comparisons

As shown in Table 1, the sample periods differ among the markets which makes direct comparisons difficult. Yet it is useful to know which markets exhibit a stronger relationship between temperatures and stock returns. To this end, we repeat all the analyses for the (longest possible) common sample period which is from January 2, 1989 to December 31, 1999. It turns out that all the previously identified relationships remain true, albeit some estimates become less significant due to a shorter sample period. For brevity, we only report the one-pass regression results in Table 10. Comparing Table 10 with Table 6, we see that the overall qualitative conculsions remain the same. The HDD coefficient becomes even more significant for certain markets (e.g. Canada). More importantly, within Table 10, we could now make direct comparisons. Judging by t-values, Sweden sees the strongest relation between returns and HDDs, followed by the U.S., Germany, Canada, and Britain. Japan and Taiwan still see a positive, though statistically insignificant relation between HDDs and stock returns, whereas the HDD coefficient for Australia becomes negative and close to zero. By examining the standard deviations and temperature ranges in Table 1, we immediately see that countries with a bigger temperature variation in the winter tend to see a stronger relationship between the temperature and the market returns. Indeed, Australia, Japan and Taiwan have a relatively small temperature variation, especially in terms of the termperature range. In places where people can distinctly feel the temperature changes, the market returns tend to be more closely correlated with the temperature. This observation again reinforces our hypothesis about the general impact of tempertures on investors' behaviour.

4.5. Sub-sample results

To provide some evidence on the intertemporal stability of the relationship between temperatures and returns, we repeat the analyses for sub-samples. Since the time series for the New York Stock Exchange (both equally weighted and value-weighted indices) has the longest sample period, we will focus on this market. Starting from 1999 and going backwards, we cut the entire sample into three 11-year sub-periods.[7] Bin tests and regression analyses are performed for each sub-sample and each index. By and large, the qualitative relationship between temperatures and market returns is quite stable across time. Quantitatively, estimation coefficients do not necessarily stay constant over time. To demonstrate this point, we report the one-pass regression results in Table 11. It is seen that, for both indices, the coefficient for the HDD variable seems to be on the rise. This is just by chance since sub-sample analyses for other markets failed to produce similar results.

[7] We choose 11 years (as opposed to the longest possible 12 years) as the length for the sub-samples for the sake of consistency: the last sub-period coincides with the sample period in Table 10.

4.6. Aggregating temperature impacts across regions

It is obvious 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 a different weather condition (be it subshine or temperature) than that in New York. Therefore, similar to the sunshine study of Hirshleifer and Shumway (2001), 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 Angelas, New York, Philadelphia, and Seattle. The daily temperature data for all cities other than New York come from the National Climatic Data Center, 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.[8] Bin test and regression analyses are then performed using the CRSP indices and the aggregate temperature indices. In Table 12, we report the bin test for both the HDD and the CDD variables in Panel A, and the one-pass regression results in Panel B.

It is seen that the general observations for New York city alone in Tables 2, 3 and 5 are also obtained here, albeit the statistical significance for most estimates is now lower, as expected. For

[8]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).

the HDD variable, statistical significance is mostly preserved. Analyses based on the population-weighted temperature index tend to produce a higher statistical significance for the estimates, due to the relatively larger population in the "colder cities" such as New York and Chicago. The most important implication is 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. Granted that investors are scattered around the country, but they are subject to very similar temperature variations, thanks to the high correlations between regional temperatures. [9]

At this point, we can conclude that there is indeed a "temperature anomaly" in the stock markets, and we have been able to confirm our hypothesis. Specifically, higher stock returns are related to low temperatures, and lower returns are related to higher temperatures, with the former relationship being much stronger than the latter statistically. The results are robust to many different alternative specifications and are stable over time.

5. Summary and Conclusion

The psychological literature shows that temperature is one of the important meteorological variables that affect people's mood. Mood in turn regulates behavior. It is known that low temperatures tend to cause aggression, and high temperatures tend to cause aggression, hysteria, and apathy. It is only natural to conjecture that temperature variations would cause investors to alter their investment behavior.

Existing research has revealed that stock market returns are related to such variables / events as the amount of sunshine (Saunders, 1993; Hirshleifer and Shumway, 2001), the daylight-savings time change (Kamstra, Kramer and Levi, 2000), the length of the night (Kamstra, Kramer and

[9] For instance, the correlation between daily temperatures of New York and Chicago is 0.8964. See Cao and Wei (2002) for other properties of daily temperatures.

Levi, 2002), and the lunar phases of the moon (Dichev and Janes, 2001; and Yuan, Zheng and Zhu, 2001). Based on some psychological and clinical evidence, these authors conjectured and hypothesized that investors' mood is affected by the above meteorological variables and the mood change causes investors to alter their investment behavior. For instance, investors feel upbeat on sunny days and are more likely to engage in buying than selling stocks (perhaps due to lower risk-aversion), which leads to a higher overall market return (Saunders, 1993; Hirshleifer and Shumway, 2001). Conversely, 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, 2002).

Following similar lines of thinking, in this study, we attempt to identify correlations between the temperature and stock market returns. The existing psychological evidence seems to suggest that lower temperatures can cause aggression, and higher temperatures can cause aggression, hysteria and apathy. We therefore hypothesize that lower temperatures lead to higher stock returns thanks 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.

By examining nine market indices for eight international markets, we have indeed uncovered a temperature anomaly. Our analyses reveal a statistically significant relation between the temperature and stock market returns: the lower the temperature, the higher the stock returns, and vice versa. The relationship is much stronger when the temperature is low. Our results are also robust to alternative definitions of temperature variables and controlling for such known anomalies as the Monday effect, the tax loss effect, the cloud cover effect, and the seasonal affective disorder effect. Thus, our empirical evidence supports the hypothesis regarding lower temperatures vis-à-vis higher stock returns, and reveals that apathy dominates aggression when the temperature is high, which results in lower stock returns.

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Appendices

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

Country / State	United States		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	$59^{0}21'$N	$33^{0}52'$N	$35^{0}41'$N	$25^{0}02'$N
Beginning	03/07/1962	03/07/1962	04/01/1977	03/04/1984	06/01/1970	02/01/1989	06/08/1984	05/01/1984	01/10/1977
Ending	31/12/1999	31/12/1999	13/03/2001	13/03/2001	09/07/2001	29/06/2001	31/12/2000	09/07/2001	09/07/2001
Panel A: Daily Percentage Return									
# of obs.	9442	9442	6097	4285	7901	3129	4145	4314	6777
Mean	0.075%	0.051%	0.015%	0.038%	0.028%	0.054%	0.036%	0.005%	0.037%
Std. Dev.	0.68%	0.82%	0.37%	0.98%	1.12%	1.43%	1.01%	1.36%	1.67%
Min	-10.48%	-17.17%	-5.12%	-13.03%	-13.71%	-7.49%	-28.71%	-16.14%	-9.71%
Max	6.94%	8.67%	3.75%	7.60%	8.86%	13.14%	5.74%	12.43%	7.58%
Skewness	-1.11	-1.12	-1.11	-0.99	-0.48	0.32	-6.16	-0.12	-0.27
Kurtosis	16.98	26.22	16.15	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

Weather stations for each city:

New York: New York Laguardia Airport,
London: London Heathrow Airport,
Stockholm: Stockholm / Bromma Airport,
Tokyo: Tokyo Airport,
Toronto: Toronto International Airport,
Frankfurt: Frankfurt Main Airport,
Sydney: Sdyney International Airport,
Taipei: Sungshan / Taipei Airport.

Table 2: Relation Between Stock Market Returns and HDDs

		# of bins = 2			# of bins = 3			
		bin 1	bin 2	z-score $_{2,1}$	bin 1	bin 2	bin 3	z-score $_{3,1}$
U.S. CRSP-EW	Return Mean	0.0006	0.0019	6.531 ***	0.0005	0.0013	0.0023	5.102 ***
	Std. Dev. of Return	0.0069	0.0064		0.0069	0.0065	0.0059	
	% of Positive Returns	0.5992	0.6689	4.727 ***	0.5956	0.6293	0.6958	3.597 ***
U.S. CRSP-VW	Return Mean	0.0005	0.0009	1.844 **	0.0004	0.0007	0.0013	1.939 **
	Std. Dev. of Return	0.0084	0.0071		0.0085	0.0074	0.0075	
	% of Positive Returns	0.5433	0.5794	2.338 ***	0.5428	0.5515	0.6294	2.965 ***
Canada	Return Mean	0.0001	0.0003	1.948 **	0.0001	0.0002	0.0004	1.588 *
	Std. Dev. of Return	0.0038	0.0035		0.0037	0.0038	0.0035	
	% of Positive Returns	0.5335	0.5737	2.565 ***	0.5356	0.5405	0.5965	2.478 ***
Britain	Return Mean	0.0001	0.0017	3.930 ***	0.0002	0.0006	0.0015	1.612 *
	Std. Dev. of Return	0.0099	0.0093		0.0101	0.0095	0.0086	
	% of Positive Returns	0.5186	0.5820	3.083 ***	0.5223	0.5340	0.5920	1.547 *
Germany	Return Mean	0.0002	0.0006	1.244	0.0000	0.0006	0.0017	2.638 ***
	Std. Dev. of Return	0.0113	0.0111		0.0113	0.0113	0.0101	
	% of Positive Returns	0.5145	0.5295	0.972	0.5067	0.5292	0.5677	1.953 **
Sweden	Return Mean	0.0003	0.0021	2.483 ***	0.0002	0.0009	0.0033	2.082 **
	Std. Dev. of Return	0.0143	0.0142		0.0138	0.0150	0.0121	
	% of Positive Returns	0.5174	0.5754	2.258 **	0.5109	0.5387	0.6377	2.145 **
Australia	Return Mean	0.0003	0.0006	0.593	0.0003	0.0004	0.0008	0.789
	Std. Dev. of Return	0.0104	0.0082		0.0108	0.0079	0.0082	
	% of Positive Returns	0.5238	0.5490	1.140	0.5282	0.5163	0.5661	1.020
Japan	Return Mean	-0.0001	0.0006	1.656 **	-0.0001	-0.0001	0.0016	2.714 ***
	Std. Dev. of Return	0.0139	0.0127		0.0139	0.0135	0.0121	
	% of Positive Returns	0.5031	0.5448	2.361 ***	0.5030	0.5112	0.5831	3.159 ***
Taiwan	Return Mean	0.0004	0.0043	1.251	0.0003	0.0034	0.0050	23.122 ***
	Std. Dev. of Return	0.0165	0.0084		0.0165	0.0151	0.0000	
	% of Positive Returns	0.5038	0.7143	1.232	0.5014	0.6296	1.0000	81.260 ***

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

Table 3: Relation Between Stock Market Returns and CDDs

		# of bins = 2			# of bins = 3			
		bin 1	bin 2	z-score $_{2,1}$	bin 1	bin 2	bin 3	z-score $_{3,1}$
U.S. CRSP-EW	Return Mean	0.0008	0.0004	-1.631 *	0.0008	0.0006	0.0004	-0.899
	Std. Dev. of Return	0.0069	0.0059		0.0069	0.0066	0.0047	
	% of Positive Returns	0.6096	0.5813	-1.373 *	0.6084	0.6087	0.5683	-0.944
U.S. CRSP-VW	Return Mean	0.0005	0.0003	-0.853	0.0005	0.0005	0.0005	-0.015
	Std. Dev. of Return	0.0083	0.0075		0.0083	0.0081	0.0062	
	% of Positive Returns	0.5485	0.5369	-0.554	0.5438	0.5682	0.5683	0.580
Canada	Return Mean	0.0001	0.0002	0.473	0.0001	0.0003	0.0003	0.383
	Std. Dev. of Return	0.0037	0.0026		0.0037	0.0033	0.0022	
	% of Positive Returns	0.5421	0.5276	-0.366	0.5423	0.5368	0.5122	-0.384
Britain	Return Mean	0.0004	-0.0012	-1.397 *	0.0004	-0.0003	-0.0027	-1.182
	Std. Dev. of Return	0.0099	0.0080		0.0099	0.0091	0.0097	
	% of Positive Returns	0.5303	0.3958	-1.894 **	0.5295	0.5347	0.2857	-2.015 **
Germany	Return Mean	0.0003	-0.0010	-1.660 **	0.0003	0.0002	-0.0014	-1.175
	Std. Dev. of Return	0.0113	0.0108		0.0113	0.0105	0.0116	
	% of Positive Returns	0.5176	0.4866	-0.838	0.5171	0.5102	0.5303	0.214
Sweden	Return Mean	0.0006	-0.0005	-0.511	0.0006	-0.0014	0.0014	0.239
	Std. Dev. of Return	0.0143	0.0112		0.0143	0.0103	0.0105	
	% of Positive Returns	0.5257	0.5000	-0.280	0.5260	0.4524	0.6667	0.894
Australia	Return Mean	0.0004	-0.0012	-2.082 **	0.0003	0.0007	-0.0018	-1.496 *
	Std. Dev. of Return	0.0101	0.0096		0.0103	0.0086	0.0099	
	% of Positive Returns	0.5292	0.4808	-1.188	0.5263	0.5410	0.4583	-0.939
Japan	Return Mean	0.0002	-0.0008	-1.671 **	0.0001	0.0001	-0.0008	-1.252
	Std. Dev. of Return	0.0136	0.0138		0.0137	0.0131	0.0139	
	% of Positive Returns	0.5172	0.4919	-1.209	0.5158	0.5147	0.4857	-1.072
Taiwan	Return Mean	0.0006	0.0000	-1.410 *	0.0006	0.0001	0.0000	-1.082
	Std. Dev. of Return	0.0163	0.0168		0.0162	0.0168	0.0168	
	% of Positive Returns	0.5012	0.5096	0.654	0.4960	0.5143	0.5104	0.873

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

Table 4: Two-Pass Regressions With Monday Dummy, Tax-Dummy, HDDs, and CDDs

	Panel A				Panel B		
	$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \varepsilon_t$				$\varepsilon_t = \beta_1 + \beta_2 HDD_t + \beta_3 CDD_t + \eta_t$		
	α_1	α_2	α_3	α_4	β_1	β_2	β_3
U.S. CRSP-EW	0.00097	0.38196	-0.00305	0.00208	-0.00030	0.00063	0.00051
	13.3997	40.2042	-18.7034***	6.2277***	-2.4134	3.3770***	1.0821
U.S. CRSP-VW	0.00068	0.17167	-0.00147	0.00056	-0.00022	0.00046	0.00038
	7.2713	16.9618	-6.9678***	1.3036*	-1.3657	1.9098**	0.6143
Canada	0.00021	0.18895	-0.00051	0.00000	-0.00012	0.00017	0.00055
	4.0850	15.0353	-4.2603***	0.0031	-1.4426	1.7201**	0.9437
Britain	0.00055	0.07336	-0.00108	0.00021	-0.00039	0.00098	-0.00022
	3.2640	4.8139	-2.8083***	0.2690	-1.3583	1.7525**	-0.0667
Germany	0.00051	0.04218	-0.00141	0.00092	-0.00030	0.00066	-0.00048
	3.5785	3.7538	-4.4326***	1.4290*	-1.2632	1.7619**	-0.2348
Sweden	0.00041	0.06363	0.00038	0.00107	-0.00101	0.00157	0.00475
	1.4275	3.5694	0.5938	0.8105	-2.0362	2.4027***	0.6624
Australia	0.00034	0.08495	-0.00049	0.00170	-0.00015	0.00064	0.00098
	1.9413	5.4920	-1.2356	2.1693**	-0.5216	0.4272	0.6719
Japan	0.00029	0.00475	-0.00119	-0.00043	-0.00050	0.00176	0.00055
	1.2481	0.3119	-2.2653**	-0.3611	-1.2169	1.9080**	0.4475
Taiwan	0.00052	0.09987	-0.00124	0.00006	0.00014	0.00289	-0.00085
	2.3154	8.2587	-2.2694**	0.0811	0.3662	1.1596	-0.9196

Note:
1. For each market and regression, the first row contains the parameter estimates, and the second row contains the t-values.
2. *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (one-sided test). For clear presentations, we only indicate the significance for independent variables D_t^{Mon}, D_t^{Tax}, HDD_t, and CDD_t.
3. The Tax-Dummy covers the first ten trading days of the taxation year.

Table 5: One-Pass Regression With Monday Dummy, Tax-Dummy, HDDs and CDDs

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t + \alpha_6 CDD_t + \varepsilon_t$$

	α_1	α_2	α_3	α_4	α_5	α_6
U.S. CRSP-EW	0.00066	0.38051	-0.00306	0.00170	0.00069	0.00055
	5.1824	40.0417	-18.7451 ***	4.8563 ***	3.5577 ***	1.1520
U.S. CRSP-VW	0.00046	0.17115	-0.00147	0.00028	0.00051	0.00040
	2.7571	16.9070	-6.9938 ***	0.6122	2.0107 **	0.6530
Canada	0.00009	0.18847	-0.00052	-0.00012	0.00018	0.00057
	0.9690	14.9952	-4.3027 ***	-0.4853	1.7884 **	0.9717
Britain	0.00017	0.07234	-0.00108	0.00009	0.00099	-0.00023
	0.5698	4.7420	-2.8137 ***	0.1107	1.7596 **	-0.0680
Germany	0.00020	0.04180	-0.00141	0.00057	0.00071	-0.00043
	0.8387	3.7198	-4.4342 ***	0.8509	1.8384 **	-0.2111
Sweden	-0.00061	0.06154	0.00038	0.00042	0.00163	0.00485
	-1.1963	3.4500	0.5923	0.3076	2.4533 ***	0.6757
Australia	0.00019	0.08464	-0.00048	0.00166	0.00066	0.00098
	0.6313	5.4686	-1.2144	2.0145 **	0.4225	0.6732
Japan	-0.00021	0.00341	-0.00120	-0.00112	0.00189	0.00058
	-0.5070	0.2235	-2.2929 **	-0.9158	1.9889 **	0.4686
Taiwan	0.00073	0.09933	-0.00125	-0.00032	0.00282	-0.00099
	1.7718	8.2128	-2.2950 **	-0.3842	1.1306	-1.0150

Note:
1. For each market and regression, the first row contains the parameter estimates, and the second row contains the t-values.
2. *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (one-sided test). For clear presentations, we only indicate the significance for independent variables D_t^{Mon}, D_t^{Tax}, HDD_t, and CDD_t.
3. The Tax-Dummy covers the first ten trading days of the taxation year.

Table 6: Explanatory Power of HDD, CDD, Cloud Cover, and the SAD Variable

	Panel A			Panel B			
	Cloud Cover			HDD_t	CDD_t	$Cloud_t$	SAD_t
U.S. CRSP-EW	Mean	4.714	Reg 1	2.6863 ***	1.0971	--	--
(# of obs. = 4046)	Std. Dev.	2.736	Reg 2	--	--	-1.1322	-0.1127
			Reg 3	2.5150 ***	0.8868	--	--
U.S. CRSP-VW	Mean	4.714	Reg 1	1.6611 **	1.0073	--	--
(# of obs. = 4046)	Std. Dev.	2.736	Reg 2	--	--	-1.1883	0.1150
			Reg 3	1.4775 *	0.8731	--	--
UK	Mean	5.803	Reg 1	1.9864 **	0.5071	--	--
(# of obs. = 3478)	Std. Dev.	1.898	Reg 2	--	--	-1.1404	0.7480
			Reg 3	1.5819 *	0.3010	--	--
Sweden	Mean	5.403	Reg 1	2.1413 **	0.8036	--	--
(# of obs. = 2253)	Std. Dev.	1.955	Reg 2	--	--	-0.8564	-0.1974
			Reg 3	2.3028 **	0.6396	--	--
Australia	Mean	3.812	Reg 1	0.4874	0.8892	--	--
(# of obs. = 3386)	Std. Dev.	2.318	Reg 2	--	--	-2.1424 **	-0.7892
			Reg 3	-0.1199	1.0112	--	--
Taiwan	Mean	5.567	Reg 1	0.6449	-1.1091	--	--
(# of obs. = 4575)	Std. Dev.	1.978	Reg 2	--	--	0.3379	0.8481
			Reg 3	0.6373	-0.5145	--	--

Note:

1. Reg 1: $r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t + \alpha_6 CDD_t + \varepsilon_t$;
   Reg 2: $r_t = \gamma_1 + \gamma_2 r_{t-1} + \gamma_3 D_t^{Mon} + \gamma_4 D_t^{Tax} + \gamma_5 Cloud_t + \gamma_6 SAD_t + \epsilon_t$;
   Reg 3: $\widehat{\epsilon}_t = \varphi_1 + \varphi_2 HDD_t + \varphi_3 CDD_t + \xi_t$;
   where $Cloud_t$ measures the cloud cover, and SAD_t is the number of hours of night minus 12 for the period of September 21 to March 20, and zero for other time of the year; other variables are the same as in Table 6. The number of hours of night is calculated as $7.72 \cdot ar\cos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan\left(\lambda_t\right)\right]$ for the Southern Hemisphere, and that for the Northern Hemisphere is 24 minus the above quantity. In the above formula, δ is the latitude of the market location as shown in Table 1, 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 January2, and so on.
2. For each market and regression, for the sake of brevity, we only report t-values for variables HDD_t, CDD_t, $Cloud_t$, and SAD_t. *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (one-sided test).
3. The tax-dummy, D_t^{Tax} covers the first ten trading days of the taxation year.

Table 7: Relation Between Stock Market Returns and Alternatively Defined HDDs

		# of bins = 2			# of bins = 3			
		bin 1	bin 2	z-score$_{2,1}$	bin 1	bin 2	bin 3	z-score$_{3,1}$
U.S. CRSP-EW	Return Mean	0.0006	0.0021	6.104 ***	0.0005	0.0016	0.0029	4.966 ***
	Std. Dev. of Return	0.0069	0.0059		0.0069	0.0066	0.0057	
	% of Positive Returns	0.6019	0.6882	4.569 ***	0.5972	0.6474	0.7483	4.226 ***
U.S. CRSP-VW	Return Mean	0.0005	0.0010	1.617 *	0.0004	0.0008	0.0015	2.056 **
	Std. Dev. of Return	0.0083	0.0071		0.0084	0.0073	0.0065	
	% of Positive Returns	0.5443	0.5945	2.513 ***	0.5427	0.5621	0.6623	3.074 ***
Canada	Return Mean	0.0001	0.0004	1.506 *	0.0001	0.0004	0.0000	-0.528
	Std. Dev. of Return	0.0037	0.0036		0.0037	0.0036	0.0033	
	% of Positive Returns	0.5363	0.5938	2.682 ***	0.5340	0.5751	0.5652	0.839
Britain	Return Mean	0.0003	0.0015	1.720 **	0.0002	0.0016	0.0021	1.244
	Std. Dev. of Return	0.0099	0.0091		0.0099	0.0091	0.0100	
	% of Positive Returns	0.5269	0.5707	1.171	0.5198	0.5798	0.6341	1.511 *
Germany	Return Mean	0.0002	0.0011	1.710 **	0.0002	0.0005	0.0025	2.508 ***
	Std. Dev. of Return	0.0113	0.0102		0.0113	0.0113	0.0092	
	% of Positive Returns	0.5157	0.5398	0.946	0.5149	0.5204	0.6117	1.999 **
Sweden	Return Mean	0.0005	0.0029	1.726 **	0.0003	0.0021	0.0054	2.289 **
	Std. Dev. of Return	0.0143	0.0132		0.0142	0.0145	0.0101	
	% of Positive Returns	0.5232	0.5978	1.437 *	0.5199	0.5615	0.7143	1.963 **
Australia	Return Mean	0.0003	0.0006	0.593	0.0003	0.0004	0.0008	0.789
	Std. Dev. of Return	0.0104	0.0082		0.0108	0.0079	0.0082	
	% of Positive Returns	0.5238	0.5490	1.140	0.5282	0.5163	0.5661	1.020
Japan	Return Mean	-0.0001	0.0007	1.663 **	-0.0002	0.0003	0.0022	3.269 ***
	Std. Dev. of Return	0.0139	0.0126		0.0140	0.0129	0.0124	
	% of Positive Returns	0.5048	0.5459	2.183 **	0.5017	0.5175	0.6097	3.701 ***
Taiwan	Return Mean	0.0003	0.0032	1.775 **	0.0003	0.0013	0.0050	22.590 ***
	Std. Dev. of Return	0.0148	0.0118		0.0148	0.0141	0.0113	
	% of Positive Returns	0.5024	0.6769	2.993 ***	0.5007	0.5455	1.0000	79.139 ***

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. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (one-sided test).
3. HDDs are calculated based on sample average temperatures.

Table 8: One-Pass Regression With Monday Dummy, Tax-Dummy, Alternatively Defined HDDs, and CDDs

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t^{alternative} + \alpha_6 CDD_t^{alternative} + \varepsilon_t$$

	α_1	α_2	α_3	α_4	α_5	α_6
U.S. CRSP-EW	0.00077	0.38064	-0.00305	0.00167	0.00061	0.00008
	6.0376	40.0615	-18.7325***	4.7543***	3.3022***	0.4403
U.S. CRSP-VW	0.00054	0.17124	-0.00147	0.00026	0.00044	0.00006
	3.2547	16.9172	-6.9858***	0.5697	1.8485**	0.2330
Canada	0.00010	0.18867	-0.00051	-0.00016	0.00015	0.00006
	1.0637	15.0148	-4.2877***	-0.6403	2.0956**	0.8298
Britain	0.00001	0.07067	-0.00109	0.00030	0.00185	0.00072
	0.0391	4.6333	-2.8414***	0.3736	2.9984***	1.1619
Germany	0.00020	0.04139	-0.00141	0.00043	0.00092	0.00017
	0.8311	3.6839	-4.4494***	0.6399	2.5046***	0.4525
Sweden	0.00015	0.06159	0.00037	0.00040	0.00086	-0.00022
	0.3095	3.4523	0.5828	0.2937	1.7395**	-0.4637
Australia	0.00019	0.08464	-0.00048	0.00166	0.00067	0.00099
	0.6224	5.4684	-1.2142	2.0125**	0.4320	0.6808
Japan	-0.00016	0.00338	-0.00120	-0.00115	0.00200	0.00035
	-0.3823	0.2220	-2.2909**	-0.9406	1.9729**	0.3716
Taiwan	0.00030	0.09924	-0.00126	-0.00013	0.00291	-0.00037
	0.7710	8.2059	-2.3173**	-0.1617	1.7325**	-0.1925

Note:

1. For each market, the first row contains the parameter estimates, and the second row contains the t-values.
2. *, **, and *** indicate stastistical significant at the 10%, 5% and 1% levels respectively (one-sided test). For clear presentations, we only indicate the significance for independent variables D_t^{Mon}, D_t^{Tax}, $HDD_t^{alternative}$, and $CDD_t^{alternative}$.
3. The Tax-Dummy covers the first ten trading days of the taxation year.

Table 9: Relation Between Stock Market Returns and Positive HDD Deviations

		# of bins = 2			# of bins = 3			
		bin 1	bin 2	z-score $_{2,1}$	bin 1	bin 2	bin 3	z-score $_{3,1}$
U.S. CRSP-EW	Return Mean	0.0008	0.0020	2.628 ***	0.0007	0.0013	0.0028	2.731 ***
	Std. Dev. of Return	0.0071	0.0060		0.0072	0.0064	0.0050	
	% of Positive Returns	0.6032	0.6859	2.386 ***	0.6003	0.6282	0.8222	3.846 ***
U.S. CRSP-VW	Return Mean	0.0004	0.0017	2.510 ***	0.0004	0.0009	0.0018	1.556 *
	Std. Dev. of Return	0.0082	0.0065		0.0084	0.0069	0.0059	
	% of Positive Returns	0.5335	0.6545	3.410 ***	0.5284	0.5886	0.6667	1.951 **
Canada	Return Mean	0.0002	0.0000	-0.562	0.0002	-0.0001	0.0003	0.165
	Std. Dev. of Return	0.0037	0.0028		0.0036	0.0037	0.0025	
	% of Positive Returns	0.5431	0.5847	0.899	0.5437	0.5450	0.6522	1.086
Britain	Return Mean	0.0003	0.0026	2.067 **	0.0003	0.0005	0.0091	3.697 ***
	Std. Dev. of Return	0.0097	0.0089		0.0099	0.0088	0.0083	
	% of Positive Returns	0.5215	0.6866	2.860 ***	0.5224	0.5379	0.9167	4.889 ***
Germany	Return Mean	0.0001	0.0018	1.999 **	0.0000	0.0007	0.0029	2.515 ***
	Std. Dev. of Return	0.0114	0.0105		0.0113	0.0114	0.0078	
	% of Positive Returns	0.5111	0.5793	1.730 **	0.5103	0.5227	0.6596	2.142 **
Sweden	Return Mean	0.0004	0.0030	1.307 *	0.0004	0.0004	0.0060	1.506 *
	Std. Dev. of Return	0.0146	0.0116		0.0146	0.0138	0.0122	
	% of Positive Returns	0.5157	0.5556	0.475	0.5133	0.5440	0.6364	0.845
Australia	Return Mean	0.0003	0.0006	0.309	0.0003	0.0007	-0.0010	-0.703
	Std. Dev. of Return	0.0120	0.0092		0.0127	0.0082	0.0106	
	% of Positive Returns	0.5280	0.4750	-1.111	0.5272	0.5169	0.4706	-0.651
Japan	Return Mean	0.0004	0.0007	0.141	0.0006	-0.0006	0.0021	0.306
	Std. Dev. of Return	0.0134	0.0144		0.0134	0.0134	0.0161	
	% of Positive Returns	0.5284	0.5161	-0.189	0.5261	0.5391	0.4545	-0.474
Taiwan	Return Mean	0.0010	0.0094	1.892 **	0.0009	0.0037	0.0050	8.133 ***
	Std. Dev. of Return	0.0168	0.0062		0.0169	0.0134	0.0000	
	% of Positive Returns	0.5272	1.0000	32.767 ***	0.5229	0.6585	1.0000	32.491 ***

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. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (one-sided test).
3. Bins are constructed based on positive deviations of realized HDDs from historical average HDDs.

Table 10: One-Pass Regression With Equal Sample Period (02/01/1989 - 31/12/1999)

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t + \alpha_6 CDD_t + \varepsilon_t$$

	α_1	α_2	α_3		α_4		α_5		α_6
U.S. CRSP-EW	0.00089	0.30349	-0.00238		0.00053		0.00090		0.00008
	4.2248	16.7694	-8.8987	***	0.9263		2.6764	***	0.1161
U.S. CRSP-VW	0.00031	0.07509	0.00016		-0.00129		0.00096		0.00005
	1.0142	3.9648	0.4200		-1.5595	*	1.9567	**	0.0452
Canada	-0.00006	0.18645	-0.00003		-0.00016		0.00031		0.00027
	-0.5845	9.9790	-0.2237		-0.5220		2.3652	***	0.3990
Britain	0.00007	0.07654	-0.00040		0.00044		0.00119		-0.00094
	0.2063	4.0401	-0.9215		0.4812		1.8030	**	-0.2711
Germany	-0.00023	0.01236	0.00034		-0.00124		0.00184		-0.00027
	-0.5026	0.6496	0.5711		-0.9864		2.4499	***	-0.0809
Sweden	-0.00049	0.08797	0.00010		0.00020		0.00181		0.00382
	-0.9620	4.6389	0.1565		0.1471		2.7559	***	0.5686
Australia	0.00029	0.05252	-0.00047		0.00159		-0.00009		-0.00008
	0.9327	2.7711	-1.1370		1.8784	**	-0.0561		-0.0520
Japan	-0.00013	-0.01009	-0.00181		-0.00164		0.00140		0.00029
	-0.2234	-0.5259	-2.5603	***	-0.9814		1.0424		0.1738
Taiwan	0.00136	0.06156	-0.00120		-0.00192		0.00603		-0.00354
	1.8249	3.3609	-1.2424		-1.0598		1.1939		-2.0427

Note:

1. For each market and regression, the first row contains the parameter estimates, and the second row contains the t-values.
2. *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (one-sided test). For clear presentations, we only indicate the significance for independent variables D_t^{Mon}, D_t^{Tax}, HDD_t, and CDD_t.
3. The Tax-Dummy covers the first ten trading days of the taxation year.

Table 11: One-Pass Regression For the Sub-Sample Periods of the U.S. CRSP index

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t + \alpha_6 CDD_t + \varepsilon_t$$

	α_1	α_2	α_3		α_4		α_5		α_6
			CRSP Equally Weighted Index						
1967 - 1977	0.00043	0.45673	-0.00314		0.00230		0.00064		0.00080
	1.6855	26.8658	-9.6246	***	3.2577	***	1.6754	**	0.7696
1978 - 1988	0.00075	0.35191	-0.00387		0.00181		0.00068		0.00103
	3.0174	19.9250	-12.0189	***	2.6132	***	1.8330	**	1.0952
1989 - 1999	0.00089	0.30349	-0.00238		0.00053		0.00090		0.00008
	4.2248	16.7694	-8.8987	***	0.9263		2.6764	***	0.1161
			CRSP Value Weighted Index						
1967 - 1977	0.00048	0.30117	-0.00219		0.00065		0.00026		-0.00024
	1.6626	16.6039	-6.0105	***	0.8276		0.6070		-0.2061
1978 - 1988	0.00058	0.14903	-0.00230		0.00091		0.00050		0.00160
	1.6591	7.9730	-5.1349	***	0.9407		0.9593		1.2211
1989 - 1999	0.00031	0.07509	0.00016		-0.00129		0.00096		0.00005
	1.0142	3.9648	0.4200		-1.5595	*	1.9567	**	0.0452

Note:
1. For each regression, the first row contains the parameter estimates, and the second row contains the t-values.
2. *, **, and *** indicate stastistical significance at the 10%, 5% and 1% levels respectively (one-sided test). For clear presentations, we only indicate the significance for independent variables D_t^{Mon}, D_t^{Tax}, HDD_t, and CDD_t.
3. The Tax-Dummy covers the first ten trading days of the taxation year.

Table 12: Aggregate Bin Test and Regression Analysis for the U.S. CRSP Index

Panel A: Bin Test

		HDD				CDD			
		bin 1	bin 2	bin 3	z-score $_{3,1}$	bin 1	bin 2	bin 3	z-score $_{3,1}$
CRSP-EW, TEMP-EW	Return Mean	0.0006	0.0016	0.0021	2.2681 **	0.0010	0.0007	0.0005	-1.6033 *
	Std. Dev. of Return	0.0062	0.0057	0.0061		0.0064	0.0052	0.0054	
	% of Positive Returns	0.6175	0.6516	0.7340	2.5079 ***	0.6324	0.6319	0.5955	-1.2625
CRSP-EW, TEMP-PW	Return Mean	0.0007	0.0015	0.0022	2.8998 ***	0.0010	0.0008	0.0007	-0.7174
	Std. Dev. of Return	0.0063	0.0056	0.0055		0.0064	0.0050	0.0055	
	% of Positive Returns	0.6181	0.6500	0.7193	2.3500 ***	0.6285	0.6471	0.5957	-1.0668
CRSP-VW, TEMP-EW	Return Mean	0.0005	0.0011	0.0008	0.3119	0.0006	0.0008	0.0001	-1.1309
	Std. Dev. of Return	0.0087	0.0076	0.0096		0.0088	0.0076	0.0073	
	% of Positive Returns	0.5479	0.5529	0.6064	1.1403	0.5473	0.5614	0.5566	0.3146
CRSP-VW, TEMP-PW	Return Mean	0.0005	0.0009	0.0012	0.7623	0.0006	0.0009	0.0004	-0.3956
	Std. Dev. of Return	0.0088	0.0076	0.0087		0.0088	0.0076	0.0074	
	% of Positive Returns	0.5507	0.5439	0.6140	1.3605 *	0.5430	0.5868	0.5415	-0.0489

Panel B: Regressions

$$r_t = \alpha_1 + \alpha_2 r_{t-1} + \alpha_3 D_t^{Mon} + \alpha_4 D_t^{Tax} + \alpha_5 HDD_t + \alpha_6 CDD_t + \varepsilon_t$$

	α_1	α_2	α_3	α_4	α_5	α_6
CRSP-EW, TEMP-EW	0.00079	0.32605	-0.00291	0.00138	0.00871	0.00609
	4.1902	22.0135	-12.7519 ***	2.8051 ***	2.4897 ***	0.8339
CRSP-EW, TEMP-PW	0.00075	0.32575	-0.00291	0.00136	0.00876	0.00762
	4.0703	21.9911	-12.7610 ***	2.7888 ***	2.7195 ***	1.0545
CRSP-VW, TEMP-EW	0.00036	0.12036	-0.00076	-0.00003	0.00825	0.00955
	1.2949	7.7113	-2.2547 **	-0.0460	1.5895 *	0.8825
CRSP-VW, TEMP-PW	0.00032	0.12026	-0.00076	-0.00005	0.00850	0.01136
	1.1633	7.7051	-2.2637 **	-0.0757	1.7783 **	1.0608

Note:

1. This table presents bin test and regression results for the U.S. CRSP index (equally-weighted or value-weighted) and the aggregate temperature which is either equally 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. $z\_score^{mean}_{k,1} = (\mu_k - \mu_1)/\sqrt{\frac{\sigma_k^2}{n_k} + \frac{\sigma_1^2}{n_1}}$ 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.
3. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively (one-sided test). For the regression test, we only indicate the significance for independent variables D_t^{Mon}, D_t^{Tax}, HDD_t, and CDD_t.
4. The Tax-Dummy covers the first ten trading days of the taxation year.

Figure 1: Historical Daily Average Temperature

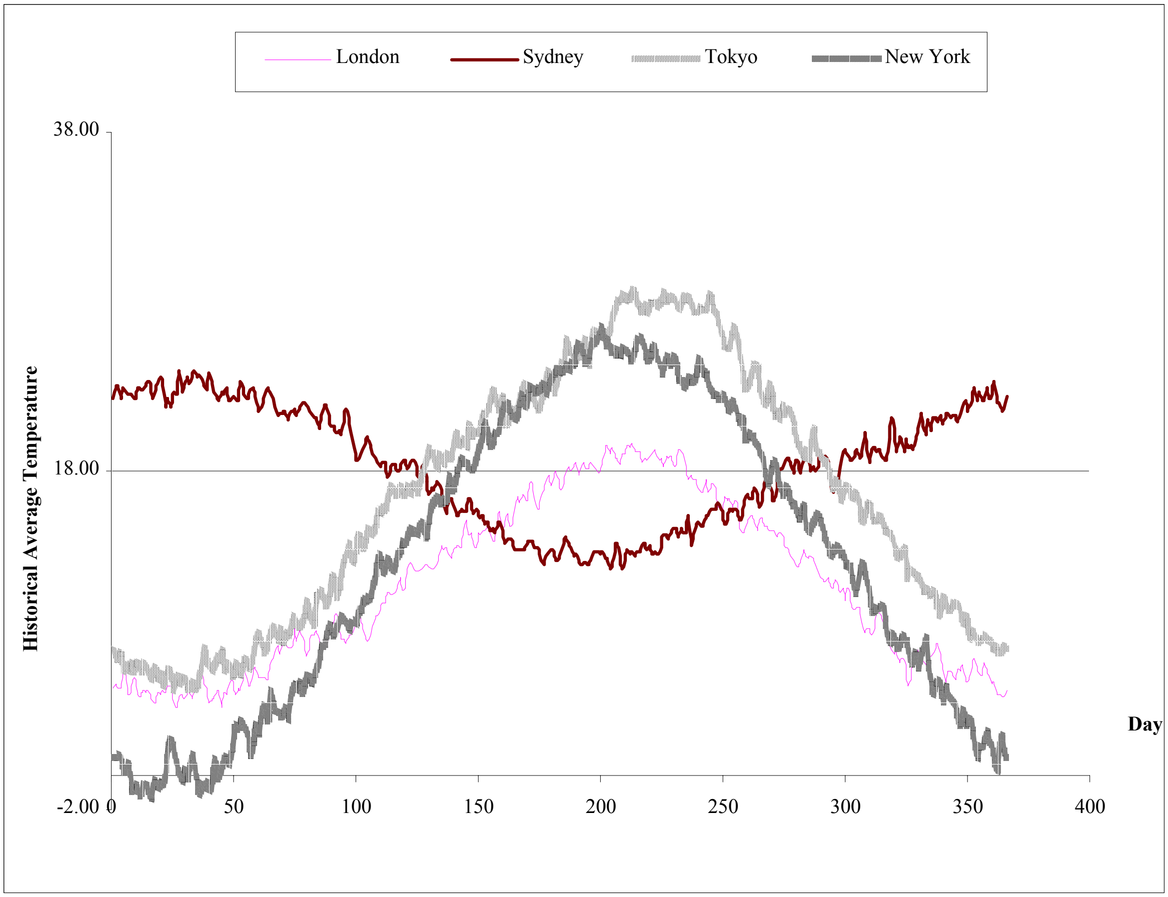

Figure 2: Historical Daily Average Heating-Degree-Days