“Is It The Weather?”

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Keywords: Stock market seasonality, Sell in May, Seasonal Affective Disorder, temperature, spurious correlations

JEL classification: G10, G12

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Abstract

We show that results in the recent strand of the literature that tries to explain stock returns by weather induced mood shifts of investors might be data-driven inference. More specifically, we consider two recent studies (Kamstra, Kramer and Levi, 2003a and Cao and Wei, 2004) that claim that a seasonal anomaly in stock returns is caused by mood changes of investors due to lack of daylight and temperature variations, respectively. We confirm earlier results in the literature that there is indeed a strong seasonal effect in stock returns in many countries: stock market returns tend to be significantly lower during summer and fall months than during winter and spring months. However, we also show that at best, these two studies offer two of many possible explanations for the observed seasonal effect. As an illustration we link ice cream production and airline travel to the same stock market seasonality using similar reasoning. Our results suggest that without any further evidence the correlation between weather variables and stock returns might be spurious and the conclusion that weather affects stock returns through mood changes of investors is premature.

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Starting with the seminal paper of Saunders (1993) a new and interesting strand of research has evolved that investigates the possible impact of weather variables on investor behavior. Saunders (1993) and Hirshleifer and Shumway (2003) find a strong relation between cloud cover and stock returns. Kamstra, Kramer and Levi (2000) report lower stock returns after weekends with daylight savings time changes. Dichev and Janes (2003) and Yuan, Zheng and Zhu (2001) relate stock returns to lunar phases. More recently, Kamstra, Kramer and Levi (2003a) find evidence of a relation between potential mood changes of investors due to a seasonal affective disorder and stock returns and Cao and Wei (2004) link stock market returns to temperature variations.

In general these studies tend to argue that weather influences the mood of investors, which in turn influences stock returns. Most studies roughly take the following approach: they cite several psychological studies that support the idea that a weather variable does affect mood in a certain way, link the mood change to either a change in risk aversion (Kamstra, Kramer and Levi, 2000, 2003a) or a type of misattribution (Saunders, 1993 and Hirshleifer and Shumway, 2003) and proceed by testing the hypothesized relation between the weather variable in question and stock returns directly. While intuitively appealing, the question is whether this approach is sound enough to establish the link between weather induced mood changes and stock returns or results in nothing more than data-driven inference based on spurious correlations. That this might be the case for the studies using cloud cover is illustrated in recent work of Goetzmann and Zhu (2002). They find a strong correlation between stock returns and cloud cover. However, when they consider trading accounts of individual investors they find no evidence that their trading behavior is influenced by the degree of cloud cover.[1]

In this study we take a closer look at the studies by Kamstra, Kramer and Levi (2003a) and Cao and Wei (2004). These studies find a similar seasonal pattern in stock returns as in Bouman and Jacobsen (2002). Bouman and Jacobsen (2002) document the existence of a strong seasonal pattern based on an old market wisdom 'Sell in May and go away': stock returns tend to be significantly lower during summer/fall months than during winter/spring months.[2] While they suggest that the effect could be caused by vacation behavior of investors, they leave the anomaly as a puzzle to be explained. Kamstra, Kramer and Levi (2003a) document a more or less similar pattern in stock returns. They argue that investors suffering from a seasonal affective disorder (SAD) might cause this seasonal pattern. Due to a lack of sunlight investors might become depressed during the fall months and require higher risk premia during the winter

[1] Moreover, note that Pardo and Valor (2003) find no evidence of any influence of cloud cover and humidity levels on Spanish index returns.
[2] This formulation is somewhat imprecise because summer and winter months depend on whether a country lies in the Northern or Southern Hemisphere. We consider this issue in more detail below.

months. Finally, Cao and Wei (2004) hypothesize that temperature influences stock market returns as some psychological studies show that extreme weather changes human behavior. Cao and Wei (2004) find an inverse relation between temperature and stock market changes. As in most countries temperature tends to be higher during summer than winter periods, the resulting pattern in stock returns tends to be similar to the ones in Bouman and Jacobsen (2002) and Kamstra, Kramer and Levi (2003a). Thus, while stating different potential causes, the studies more or less agree on the same seasonal pattern. Stock returns tend to be significantly lower during summer months (i.e. from May through October).

In this study we examine this novel stock market seasonality and its possible explanations in some detail. Our results on international stock market data confirm the general result in the three aforementioned studies: there is indeed a strong and robust seasonal pattern in stock returns. A pattern that is not only statistically significant, but also economically significant in most countries in our study. We also show, similar to Kamstra, Kramer and Levi (2003a), that the SAD variable and stock returns are highly correlated, and similar to Cao and Wei (2004) that an inverse relation between temperatures and stock returns exists. These earlier results hold even though we consider longer time periods, more countries and monthly data instead of noisier daily data used in Kamstra, Kramer and Levi (2003a) and Cao and Wei (2004).

However, more importantly, we show that due to the small differences between the different potential causes, it is not so easy to differentiate between the possible explanations reported. It seems that three explanations: an old market wisdom, SAD and temperature are in fact all possible explanations for the same seasonal pattern. For instance, by including a dummy for the Sell in May effect, there is no additional information to be gained from the inclusion of temperature or a SAD effect as explanatory variables. The same conclusion holds for the temperature variable and to a lesser extent for the SAD variable[3]. Including one of the three variables makes the other two redundant. We further show that cross-sectional evidence across countries does not favor one of the relations suggested and that it is not possible to distinguish conclusively between these potential effects using the difference between the Northern and Southern Hemispheres. Also differences in the strength of these effects in different periods do not discriminate between the explanations offered. This not only shows that more research is needed to discriminate between the three possible explanations, but also that there could be a completely different explanation that might be the actual cause for the observed seasonal pattern. Put differently, it could well be that any variable that shows a strong summer/winter seasonal effect can be used as explanatory variable. Lots of things are correlated with the seasons and it is hard to distinguish between them when trying to 'explain' seasonal patterns in

[3] We report some evidence that using only the SAD effect leaves some seasonality in the data.

stock returns. To illustrate this point we show that ice cream production in the United States and air travel data for the UK also 'explain' the same pattern in stock returns.

Our results signify that we should be careful in assuming that a relation between weather variables and stock returns exists and more generally that one should be careful in explaining stock market returns too quickly as a result of weather induced mood changes of investors. This assumption might be premature and, while plausible, a more thorough method is needed to avoid data-driven inference. This is important as, for instance, recently some studies appeared (see, for example, Kamstra, Kramer, Levi 2003b, Diao and Levi, 2004 and Garrett, Kamstra and Kramer, 2004) based on the presupposition of a SAD effect while at the moment it is questionable whether SAD is truly causing this seasonal anomaly. In fact, a practical implication of our results for future research is that it is preferred to model this seasonality using a simple seasonal dummy until we have further evidence on the probable cause of this seasonality. In that case one does not need temperature data, but may be more importantly one does has the danger of incorrectly assuming a wrong cause for the observed seasonality in stock returns.

The remainder of this study is organized as follows. In section 1 we discuss relevant literature on the stock market seasonality. In section 2 we discuss our data and empirical results. Section 3 concludes.

1. Literature Overview

Bouman and Jacobsen (2002) test whether there is some truth in the old, and in Europe well-known, market wisdom 'Sell in May and go away'. In the United States a related indicator known as the Halloween indicator also suggests that stock returns should be higher during the winter months (November through April) than during the remainder of the year (May-October period). Bouman and Jacobsen (2002) analyze 37 stock markets and find that a strong Sell in May effect is indeed present in stock market returns. They basically use three different datasets. The MSCI monthly total return series over the period 1970-1998, for the developed markets, MSCI total returns series for emerging markets over the period 1988-1998, and for several developed markets they use additional longer series that end in 1969. They find that the effect is robust over time, economically significant, unlikely to be caused by data mining, not related to risk and robust to the January effect. In addition, they show that the effect is not related to specific sectors but country specific and cannot be explained by changes in interest rates or trading volume differences in summer and winter. Bouman and Jacobsen (2002) note that the effect is predominantly present in European markets and report some evidence that the effect might be related to changes in risk aversion or changes in liquidity due to vacations. They find that the relative strength of the effect in different countries is related to some proxies for the timing and length of summer vacations. Countries with a strong summer vacation tradition exhibit the effect most strongly. However, they leave the seasonal anomaly as a puzzle to be explained.

Kamstra, Kramer and Levi (2003a) document the existence of a SAD effect in stock returns. SAD refers to a seasonal affective disorder, whereby the decreasing hours of daylight during the fall makes investors become depressed. According to Kamstra, Kramer and Levi (2003a) experimental psychological research indicates that depression leads to higher risk aversion. They argue that stock returns during the fall should become lower and relatively higher during the winter months when days start to lengthen. Kamstra, Kramer and Levi (2003a) use daily data of indices of nine stock markets with different sample periods.[4] The longest series they consider is the S&P 500 for the United States, which spans almost 70 years. The shortest series is for New Zealand, which starts in 1991 and ends in 2001. They model the hours of daylight over the year using standard approximations from spherical trigonometry. The resulting pattern is a sinusoid with a decreasing number of hours daylight during the summer and fall period and increasing number of hours daylight during the winter and spring months. The amplitude of this function depends on the latitude of the specific countries: the closer each country to the equator, the smaller the amplitude. In addition, by including a dummy for the fall months they allow for the possibility that the SAD effect is asymmetric[5]: it might affect investors differently during the fall months relative to the winter months. They find a statistically significant SAD effect in all countries they consider but Australia.[6] While they argue that the effect seems to be somewhat stronger for countries further away from the equator, this cross-sectional evidence is not very strong, given the limited number of countries they consider and different time periods used. They show that the effect is robust with respect to short-term autocorrelation, the Monday effect, the tax effect and several weather variables. The weather variables are: percentage cloud cover, millimeters of precipitation and temperature. The temperature variable is interesting as it allows a comparison with the Cao and Wei (2004) study. In a regression with all variables they find a SAD effect, but no strong evidence of a temperature effect. For the US the effect of temperature is mixed. For the other countries they only report a significant temperature effect (in addition to the SAD effect) for New Zealand and South Africa.

[4] They consider data for Australia, Canada, Germany, Japan, New Zealand, South Africa, Sweden, the United Kingdom and the United States. For the United States they consider four different market indices.

[5] Kelly and Meschke (2004) suggest that the inclusion of this dummy might lead to spurious significant results (see also footnote 13). In addition, the fall dummy might pick up effects completely unrelated to SAD.

[6] Kamstra, Kramer and Levi (2003b) report evidence of a seasonal SAD effect in bond returns and fund flows. In a similar fashion as in Kamstra, Kramer and Levi (2003a) they attribute these effects to a change in risk aversion due to SAD.

Cao and Wei (2004) also refer to psychological studies to motivate their study that relates stock returns to temperature changes during the year. They cite literature that finds that extreme temperatures affect human behavior. Exposure to extreme temperatures leads to aggression and more specifically high temperatures can also lead to apathy. The authors 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, depending on which mood, aggression (risk-taking) or apathy (risk-avoidance) dominates. To test for a possible link between temperature and stock market returns they make an in depth analysis of stock returns of eight countries[7] and check the robustness of their results on 21 international stock markets. As Kamstra, Kramer and Levi (2003a) they use daily data over different time periods. The longest series are for the US, starting in 1962 and ending in 1999. The shortest time-series is Sweden, for which the data range from 1989 to 2001. The authors use temperature data from Earth Satellite Corporation (EarthSat) and the National Climatic Data Center (NCDC). They test for a relation between temperature using bin tests and linear regression and find that stock returns are significantly negatively related to temperature. The control variables used are similar to the ones used in Kamstra, Kramer and Levi (2003a) (a lagged return, a Monday dummy, a tax loss dummy, a cloud variable and a SAD variable). The significance of the temperature variable is reduced when they include both a temperature and SAD variable in their regression. Moreover, somewhat surprisingly, they find little evidence of a significant SAD effect.

While these three studies agree that there is a strong seasonal anomaly present in stock returns, the three studies suggest different causes based on different types of evidence. Bouman and Jacobsen (2002) suggest changing risk aversion due to vacation behavior based on cross-sectional results across different countries. The other two studies link weather variables to stock returns using time-series evidence within different countries. The underlying assumption of the latter two studies is that weather influences (investor) behavior and investor behavior influences stock returns. The question immediately pops up whether or not the link between weather and behavior is as strong and clear-cut as the authors suggest.[8] For instance, a problem in the reasoning of Cao and Wei (2004) is that almost all references to experiments on temperature and human behavior study extreme warm and extreme cold temperatures; temperatures for which it is questionable that investors frequently experience these. In most countries in their study temperatures are closer to moderate temperatures. Whether small temperature changes

[7] The United States, Canada, the United Kingdom, Germany, Sweden, Australia, Japan and Taiwan.

[8] Why the amount of sunlight and temperature changes do affect behavior is discussed in a study by Parker and Tavasolli (2000). A small part of our brain, the hypothalamus, mediates the effects of sunlight and temperature on the production of hormones and neurotransmitters. Changes in the levels of both hormones and neurotransmitters change our behavior. This suggests that one could argue that both changes in sunlight and temperature do affect our behavior: we are even able to trace the effect to its physiological origin. The question that remains is whether these behavior changes caused by changes in our hormone levels and neurotransmitters are strong enough to be noticeable in stock returns.

also have a noticeable effect on human behavior and thus stock returns remains questionable. A recent study, Theissen (2003), finds no evidence that stock market predictions by German private investors are influenced by differences in temperature on the different days that these predictions were made.

The psychological links that Kamstra, Kramer and Levi (2003a) suggest, have recently been criticized by Kelly and Meschke (2004). They claim that the psychological evidence linking the time-varying depression to time-varying risk aversion has not yet been established. They also claim that other studies found that depression peaks due to SAD did not occur during the fall but during the period December-February. Moreover, psychological studies in Parker and Tavasolli (2000) find the opposite behavior to changes in sunlight than Kamstra, Kramer and Levi (2003a). Parker and Tavasolli (2000) argue that not depressed people but people in positive moods seem to become more risk averse. The reason being that they have the emotional goal of maintaining their mood. Even stronger, Parker and Tavasolli (2000) indicate that lack of sunlight might arouse risk-taking behavior. Finally, most investors working indoors are protected from the changes in temperatures and other weather conditions. That this might reduce the impact of weather variables on mood is for instance shown in Cunningham (1979). He finds that temperature is an important variable in affecting mood (the willingness to help others) in an outdoor experiment but it does not show up significantly in an indoor experiment with varying outdoor temperature.[9]

A striking difference between Cao and Wei (2004) and Kamstra, Kramer and Levi (2003a) is that the latter include a temperature variable in addition to the SAD variables and find no significant temperature effect. This seems to contradict the results in Cao and Wei (2004). However, Kamstra, Kramer and Levi (2003a) estimate a regression with a temperature and SAD variable jointly, so near multi-collinearity could be a problem. Cao and Wei (2004), in an earlier version of the paper, seemed to realize this potential problem. In that version they employed a two-stage regression. First, they removed the effect of the control variables from the return series. In the second stage they tested whether the residuals from the first regression still exhibit a significant temperature effect. The results indicated no significant SAD effect, but a temperature effect – although weaker – remained present. However, the statistical significance in these regressions is somewhat hard to judge as Cao and Wei (2004) do not correct for potential heteroscedasticity in the data. It is well known that using daily data with normal standard errors can lead to spurious significant results. Why both Cao and Wei (2004) and Kamstra, Kramer and Levi (2003a) (only) use daily data remains unclear. It is well known, that daily

[9] An additional implicit assumption of both studies is that they consider the influence of the variables at the location of the stock exchange or at least the country itself. This assumes that this is the dominating weather effect for traders at the stock market in question even though investors located in foreign countries might trade there. While plausible, this is not necessarily always the case. This last point can also be argued with respect to the Bouman and Jacobsen (2002) when they link the effect to vacations.

data are considerably noisier than for instance monthly data which is also noted by Garrett, Kamstra and Kramer (2004). Daily data are for instance hampered by non-synchronous trading problems, strong time-varying volatility, skewness and excess kurtosis. It would seem more natural to study data at a lower frequency, especially because we are interested whether these mood effects could manifest themselves in the longer run. An additional advantage is that these low frequency data are generally available over longer periods, which further reduces the chances of spurious results. If SAD or temperature has a strong impact one would expect that it shows up using monthly data as well.

Summing up, recent research so far has shown a strong seasonal effect in stock returns; an effect that could have many causes. Two recent studies suggest that this seasonal effect might be caused by weather induced mood changes of investors. Although it seems that the evidence in psychological studies is not as conclusive as one would like. This poses some interesting questions for further research which we will address in the next section.

2. Data and Empirical Results

The conflicting results and conclusions between the three aforementioned studies give rise to some interesting questions for further research. More specifically, we want to answer the following questions:

1. Do we observe a Halloween effect, a temperature effect and a SAD effect in different countries if we look at data at the monthly frequency and over longer periods?
2. Can we distinguish, using a simple regression method, which of the explanations offered in the literature is the most likely explanation for the stock market seasonality?
3. Is there some cross-sectional information or difference between the countries on the Northern and Southern Hemisphere that will tell us which of the possible explanations is more likely?
4. Can we say anything about which of these explanations is more likely by considering the strength of the effect over time? For instance, if the effect seems to get stronger over time this would not be in favor of the SAD and temperature explanation because there is no apparent reason why people should become more influenced by these effects over time.
5. Many of things are correlated with the seasons and it might be hard to distinguish among them when trying to 'explain' seasonal patterns in stock returns. Could it be the case that another seasonal variable (like ice-cream production or the number of airline travelers) will do equally well as an explanatory variable for the stock market seasonality?

We will examine these questions in detail below.

2.1 Discussion of the data

To study the influence of the three seasonal variables on equity returns, we use the monthly returns on the value-weighted indices of Morgan Stanley Capital International (MSCI). These series are re-investment indices: dividends are re-invested at the end of every month. The longest period for which we have these data available is January 1970 - May 2004. However, for many countries these series are shorter, starting in 1988 or later. We consider 48 countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Chile, China, Colombia, Czech rep., Denmark, Egypt, Germany, Finland, France, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Jordan, Korea, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Norway, Pakistan, Philippines, Poland, Portugal, Russia, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkey, the United Kingdom, the United States and Venezuela. The temperature data are from the Global Historical Climatology Network (GHCN) database. This database, which is produced jointly by the National Climatic Data Center and Carbon Dioxide Information Analysis Center, is created from 15 source data sets.[10] Following Cao and Wei (2004), we select temperatures from the weather stations that are located close to the place where the stock exchange resides. The monthly mean temperatures are calculated, according to meteorological convention, as the average of the daily maximum and minimum temperatures.

Please insert Table 1 around here.

Table 1 contains the basic characteristics of the monthly stock return series. In addition we report the latitude of the location of the (main) stock exchange of each country and some basic characteristics of the temperature data. For the first eighteen countries we have around 400 observations for each country.[11] For the remaining thirty countries we have between 120 and 200 observations for each country. Occasionally some temperature observations were missing from the sample (some of them after a quality control by the National Climatic Data Center). The mean temperature ranges from 4.84°C in Helsinki, Finland to 28.47°C in Bangkok, Thailand. The standard deviation of the mean temperature ranges from 0.58°C in Bogota, Colombia to 9.79°C in Seoul, Korea.

[10] Including NCDC's World Weather Records, CAC's Climate Anomaly Monitoring System (CAMS), NCAR's World Monthly Surface Station Climatology, and P. Jones' temperature data base for the world.

[11] For several countries we also considered longer series obtained from Global Financial Data. These countries with corresponding starting dates are: Australia: October 1882, Belgium: January 1951, Canada: January 1934, Germany: June 1953, France: February 1900, Italy: January 1961, Japan: January 1921, Netherlands: January 1951, Spain: April 1940, United Kingdom: January 1763 and United States: January 1844. Although the results in the longer samples tended to be less significant, the results remained qualitatively similar to the results reported in this section.

2.2 Testing for the effects

To test for the existence of a Sell in May, SAD, and temperature effect we use the following regression equation:

$$r_t = \alpha + \beta S_t + \varepsilon_t \,,$$

where S_t is a seasonal variable. This variable is a dummy variable in the case of the Sell in May effect. It takes the value 1 if month t falls in the period November through April and 0 otherwise. If we want to test for the temperature effect, the seasonal variable S_t is equal to the average monthly temperature. Finally, to test the SAD effect in our data, S_t is the SAD variable reflecting the length of the night in the fall and winter relative to the mean annual length of twelve hours (see Kamstra, Kramer and Levi, 2003a).[12] We found that at the monthly level there is little evidence of a possible asymmetry in the SAD effect, so for ease of exposition we do not include an additional fall dummy in our analysis.[13] For each seasonal variable we test whether the corresponding coefficient is significantly different from zero. The results are presented in Table 2.

Please insert Table 2 around here.

In line with Cao and Wei (2004) most coefficient estimates are negative. We find a negative and significant (at the five percent significance level) temperature effect present in 26 countries. In three countries the effect is significantly positive. Like in Bouman and Jacobsen (2002) the

[12] In formula:

$$SAD_t = \begin{cases} H_t - 12 & \textit{for trading days in the fall and winter} \\ 0 & \textit{otherwise,} \end{cases}$$

$$\textit{with } H_t = \begin{cases} 24 - 7.72 \cdot \arccos(-\tan(\frac{2\pi\delta}{360})\tan(\lambda_t)) & \textit{in the Northern Hemisphere} \\ 7.72 \cdot \arccos(-\tan(\frac{2\pi\delta}{360})\tan(\lambda_t)) & \textit{in the Southern Hemisphere} \end{cases}$$

where δ represents the latitude and $\lambda_t = 0.4102 \cdot \sin\{(\frac{2\pi}{365})(\text{julian}_t - 80.25)\}$. Julian_t is a variable that represents the number of the day in the year.

[13] If we include a fall dummy we find a significant SAD effect in 19 countries. In only four of these countries we find a statistical significant fall dummy. As the fall dummy might pick up more than only the asymmetry in the SAD effect, like crashes or other effects, it seems that at the monthly level there is no firm indication of an important asymmetric effect. Moreover, Kelly and Meschke (2004) show that the SAD variable and fall dummy are collinear due to an overlap in the variables. This results in a negative correlation between the two variables and mechanically induces statistical significance. Kelly and Meschke (2004) conclude that the negative fall coefficient in Kamstra, Kramer and Levi (2003a) is due to the overlapping specification of the two variables. We did several Monte Carlo experiments with a fall dummy variable and found that if we used a random walk model with a Sell in May effect as return generating process, then assumed incorrectly that it was an asymmetric SAD effect by estimating a SAD effect with a fall dummy, this resulted (incorrectly) in a significantly negative fall dummy. Given all these potential drawbacks of the fall dummy we do not include it in our analysis here. However, just to be sure we did all our analyses using a fall dummy, resulting in qualitatively similar results. The only noteworthy difference was that we no longer found a significant SAD effect for the US market.

Halloween effect seems strong: we find it significantly present in 28 countries. And finally, confirming the results of Kamstra, Kramer and Levi (2003a), we find that the SAD variable is highly significant in many countries.[14] In 28 countries it is significant with a positive sign. In four countries it is significantly negative. Note that for countries with starting date of 1993:01 or later, we typically do not find statistical significance. Thus the power of the test seems affected by the number of observations.

The results in Table 2 answer the first question we posed in the beginning of this section: Do we still observe a Halloween effect, a temperature effect and a SAD effect in different countries if we look at data at the monthly frequency and over longer periods? The answer is: Yes, for all variables, when included in the regression individually, we find a strong significant relation if we use monthly data instead of daily data. For the temperature and SAD effect we find evidence even if we consider longer horizons and lower frequency data than used in previous studies.

2.3 Testing for the combined effects

Clearly, the obvious way to proceed would be to jointly include all explanatory variables in one regression and check which of the variables remain statistically significant. Unfortunately, that approach cannot be used in this case. If one does, nearly all the variables' coefficients become statistically insignificant. The problem is that these variables are highly correlated. Consequently, we have a situation of near multi-collinearity. Figure 1, where we compare the three variables, shows the problem. In order to emphasize the correlation between the series we have rescaled the series such that all series lie between zero and one. Moreover, we have multiplied the temperature data by minus one. Looking at Figure 1, we see that the seasonal patterns in the variables are closely related.

Please insert Figure 1 around here.

For the US, the correlation between the Halloween variable and the temperature is -0.88. The correlation between SAD and the Halloween indicator is 0.62, whereas the correlation between temperature and SAD is -0.72. For the other countries the correlations are similar. Consequently, after including more than one of these variables in the regression equation, it appears that the corresponding effects disappear. This is a typical result of near multi-collinearity.

[14] Following Kamstra, Kramer and Levi (2003a), we also experimented splitting fall and winter SAD effects by redefining the SAD variable such that one variable captures effect of SAD during fall only and another variable captures effect of SAD during winter only. The results, which can be obtained from the authors upon request, did not yield qualitative different results.

To overcome this problem we employ an orthogonalization approach, which is a useful approach to capture the incremental explanatory power of additional variables. Assuming that there is a Halloween effect, we examine whether the temperature variable or the SAD variable contains additional information that warrants inclusion in the regression. We first use the projection of the temperature variable on the Halloween variable and then use the additional information from the orthogonalized temperature variable in a regression that includes the Halloween variable. For the SAD variable we take a similar approach, but also take the temperature variable as additional variable in order to ensure that the residuals of these two equations are orthogonal. Then, we repeat the procedure where we project the other two variables on the temperature variable and the SAD variable.[15]

In formula, for each country, we estimate in a first step the following two OLS regressions:[16]

$$Temp_t = \mu + \delta May_t + \varepsilon^{temp}_{\{may\},t}$$

$$SAD_t = \eta + \gamma_1 May_t + \gamma_2 Temp_t + \varepsilon^{SAD}_{\{may,temp\},t} \ ,$$

where $Temp_t$ denotes the temperature at time t, May_t is the Sell in May dummy, and SAD_t the SAD variable as described in section 2.2. In the second step we estimate the following model:

$$r_t = \alpha + \beta_1 May_t + \beta_2 \hat{\varepsilon}^{temp}_{\{may\},t} + \beta_3 \hat{\varepsilon}^{SAD}_{\{may,temp\},t} + \varepsilon_t \ .$$

The unexplained residuals $\hat{\varepsilon}^{temp}_t$ and $\hat{\varepsilon}^{SAD}_t$ represent the portion of each country's temperature and SAD effect not explained by movements in the Sell in May variable. Similarly we interchange the role of the variables in the equations bringing forth the unexplained residuals:

$$Temp_t = \mu + \delta_1 May_t + \delta_2 SAD_t + \varepsilon^{temp}_{\{may,SAD\},t}$$

$$SAD_t = \eta + \gamma May_t + \varepsilon^{SAD}_{\{may\},t} \ ,$$

[15] We also repeated the orthogonalization approach for the alternative SAD specification including the aforementioned fall dummy. This resulted in the inclusion of an additional variable, being the fall dummy projected on the Halloween variable. The results remained qualitative equivalent and the orthogonalized fall dummy did not have any additional information warranting inclusion in the regression. Also the other specification which splits the SAD variable in a fall and winter SAD variable did not alter our conclusions.

[16] In this specification the unexplained residuals in both equations are orthogonal by construction. In a previous version of this paper we used an alternative specification in which these residuals were not necessarily orthogonal. More specifically, we applied the following two regressions: $Temp_t = \mu + \delta May_t + \varepsilon^{temp}_t$ and $SAD_t = \eta + \gamma May_t + \varepsilon^{SAD}_t$. There are no major differences that alter any of the conclusions using this specification.

and estimate the return equation including the residuals from these equations. A similar approach is employed for the weather variables as base variable. This means that for every country we ran six regressions.

For the sake of brevity we report in the second and third column of Table 3 a summary of these results.[17]

Please insert Table 3 around here.

Consider for instance the first situation where we start with a Sell in May effect as the basic variable and the residuals of the regression for the other two variables. The Sell in May effect is significant in 32 countries (second column, second row of Table 3). But assuming a Sell in May effect, the value of additional information from the temperature variable is marginal: only in five countries we find that the additional information helps in explain stock market behavior. The next row shows that after we assume there is a Sell in May effect and after we have used the additional information in the temperature variable, adding the SAD variable produces significant results in seven countries only. The same conclusion holds if we start with the temperature variable or SAD variable and then add the additional variation from the other variables. This suggests that the three studies above seem to basically measure the same seasonal effect in stock returns, the only difference is the explanation given for the observed effect.

We can use the information in the data more efficiently if we do not consider the individual countries separately but pool the information from the stock market data of the individual countries and use a similar approach as before but now using Seemingly Unrelated Regressions. In other words, it might be the case that we find explanatory power of the seasonal residuals once we consider them in a multivariate way. In columns four and five of Table 3 we report our results. For instance, if we again start with the Sell in May effect and we then jointly test the set of restrictions that the partial coefficients of the temperature and SAD residuals are zero for all countries, we obtain a Wald test statistic of 63.70 and 43.08 respectively, which are not statistically significant. The same conclusion holds if we interchange the role of unexplained residuals. In other words, assuming that there is a Halloween effect, we do not find a temperature effect or a SAD effect. Similarly, assuming there is a temperature effect, there is little evidence of a Halloween effect or a SAD effect. However, if we start with the SAD variable we find that there is some explanatory power left from either the temperature or the Sell in May variable. So using the SAD variable alone leaves some potential predictability in the data. The practical implication for future research is that, if one lacks temperature data, the easiest way to

[17] A detailed version of the results is available from the authors upon request.

model the seasonal effect is using a simple seasonal dummy variable. This also prevents that one makes an unwarranted claim that some effect is causing this seasonality in stock returns.

These results also show that finding a statistically significant relation between stock returns and weather variables does not necessarily imply that it is the case that these weather variables cause the specific behavior in stock markets at least not using simple regression methods. This answers the second question we posed. We find high correlations between the weather variables, the seasonal dummy and stock returns, but which one – if any of them – causes the effect is hard to say.

An alternative route to follow would be to consider whether we can distinguish between the different explanations using differences between Northern and Southern Hemispheres, the cross-sectional evidence across countries or a different strength of the effect in different time periods. We first consider the cross-sectional evidence.

2.4 Cross-sectional evidence

If it were temperature or SAD causing the seasonal pattern in stock returns, then one could turn to the relative strength between the different effects in the different countries to check which explanation is more likely. Temperature differences between countries and hours of daylight vary depending where the different countries are located with respect to the equator. Contrary to the Halloween dummy[18], these variables themselves adjust by nature between differences in latitudes. Consequently, one would expect the coefficients for the SAD and temperature variables to be stable across countries and to be relatively similar irrespective of where the stock markets are located. However, a close inspection of the coefficients in Table 2 suggests otherwise. If anything, the closer we get to the equator the larger the coefficients for both the SAD variable and the temperature tend to become. For instance, investors in Singapore would react strongly to temperature changes: about five times as strong as investors from Scandinavian countries. This is surprising, because the standard deviation of monthly temperatures in Singapore is smaller than one degree. One might wonder whether people in Singapore would even be aware of the generally small temperature changes. Similarly, investors in Colombia and Malaysia would according to our estimation results react strongly to marginal changes in the number of hours of daylight. In fact, if one looks at the parameter estimates for the Halloween dummy it seems that, if anything, the effect is fairly independent of the location of the country in question as these coefficient estimates for this dummy tend to be similar in all countries.

[18] The corresponding coefficient for the Halloween variable can vary with the latitude because the variable is a simple dummy variable.

Differences between results in the Northern versus Southern Hemisphere could also offer some insight in which explanation is more likely. On the Southern Hemisphere the seasons are in comparison to the Northern Hemisphere reversed, so the relative lower temperatures occur during the May-October period. Similarly, the change in the number of hours of daylight is also reversed. If the effects would cause the pattern in stock returns, one would expect no sign switch in the coefficients of the temperature variable and the SAD variable. Again, closer inspection of Table 2 reveals no such evidence. Apart from Indonesia, countries in the Southern Hemisphere show higher returns in November through April than May through October even though the summer time in that hemisphere falls in the November-April period. Even stronger, we find significant and reversed temperature and SAD effects for Brazil, South Africa, Australia and Chile in our sample. Thus, from the Northern Hemisphere countries none has a 'wrong sign', but out of the seven Southern Hemisphere countries four have a (statistically significant) negative SAD effect. This suggests that the suggested weather induced mood shifts are not responsible for the stock market seasonality.

However, while this cross-sectional evidence and the differences between the hemispheres do not seem to support a SAD effect or a temperature effect, it is not conclusive in rejecting the temperature and SAD explanation either. Not only because the number of countries on the Southern Hemisphere is fairly limited and the data available are mostly relatively short time-series. More importantly, due to cross correlation between countries, temperature and SAD effects in for instance the United States might be 'exported' to other parts in the world and be stronger than local reversed effects. It could well be that a Northern Hemisphere SAD effect is imported to Australia as a reaction of Australian traders to changes in markets in the Northern Hemisphere or traders from the Northern Hemisphere trading in countries on the Southern Hemisphere.

To get back to our question: is there some cross-sectional information or difference between the Northern and Southern Hemisphere that will tell us which of the possible explanations is more likely? The answer without any further data is 'no', but the evidence we report here does not support the evidence that it is really the weather causing this seasonality in stock returns.

2.5 Time-series evidence

An alternative way to examine what causes the anomaly is to check whether the coefficients are stable over time. If it is either SAD or temperature one would not expect the coefficients to vary drastically. Why would investors be influenced differently now than say twenty years ago? If anything we are nowadays better able and equipped to isolate ourselves from the influence of the weather (for instance through sun beds and air conditioning). Thus the influence of the weather variables should be either stable or lessen over time. To verify whether we can draw any conclusions we divide our sample in two for the countries where we have data since 1970.[19] In Table 4 we report the regression results for the two sub samples for each variable in turn.

Please insert Table 4 around here.

Table 4 shows that the seasonal effect is fairly robust to the sample period used, at least if we use the temperature or a Halloween dummy. In the first half of our sample the temperature variable is statistically significant in nine countries (out of eighteen) and in the second half in fourteen out eighteen. For the Halloween we find significant results in 12 countries and 9 countries, respectively. Results for the SAD variable are less clear. While still present in the first half of our sample (significant in nine countries) judging by statistical significance, it seems to disappear in the second half of our sample. It only remains statistically significant in five countries and only very strong for Austria. A close inspection of the estimated coefficients reveals that it is difficult to draw any serious conclusion with respect to the stability of the coefficients. If anything, we observe that the effect of temperature increases over time. In thirteen countries estimated coefficients are lower in the second half of our sample. We would expect, if it really were temperature affecting stock returns, this influence to remain constant or to decrease over time. The increasing temperature effect suggests that the temperature explanation is not plausible. For the Halloween effect we find no consistent increase or decrease estimates in the coefficients: lower in ten countries, higher in eight countries. For the SAD variable we find the same results. It seems that this analysis does not soundly confirm or reject the hypothesis that weather variables are responsible for the seasonal behavior in stock returns. This means that so far, other than finding a high correlation between SAD and stock returns and temperature and stock returns, we have found very little evidence that suggests that weather induced mood changes of investors are responsible for the observed effect. How difficult is it to find alternative explanations that also result in high correlations between stock returns and the stock market seasonality under consideration? In the next section we search for alternative ‘explanations’.

2.6 Alternative explanations

One way to verify how plausible the SAD and temperature explanations are, is to consider whether any other variable with a similar seasonal pattern might also yield similar results. This

[19] As noted before for some countries we used longer time series. We also compared these results with the results reported in the text. Again, there are no major differences that would alter any of the conclusions in favor of the weather explanations. If anything the results seem to become stronger and more significant over time.

is interesting as correlation does not necessarily mean causation.[20] To verify this we use monthly data on ice cream production in the US.[21] Figure 2 shows that (rescaled) ice cream production has a strong seasonal trend similar to the other variables. If in need of a theory one might argue that ice cream is a so-called comfort food, which people consume when they are feeling depressed (Wansink and Sangerman, 2000). Depression as argued by Kamstra, Kramer and Levi (2003a) might make people more risk averse and therefore ice cream consumption might be a good indicator of general risk aversion among investors. We only have ice cream production data, but as consumption generally follows production and ice cream is a perishable good we also use one month lagged production as an indication for consumption. Unfortunately, we only have US data available so we use these as a proxy for consumption in other countries as well, although this might, especially for the countries on the Southern Hemisphere, be incorrect.

Please insert Figure 2 here.

In addition we use detrended data on the monthly number of outbound airline travelers in the United Kingdom.[22] Clearly, the more people travel abroad the less likely they are to trade. This might be one explanation. However, one could also similarly to Bouman and Jacobsen (2002) argue that the seasonal effect might be caused by changing risk aversion due to vacation behavior or liquidity constraints due to vacation spending and use outbound travel as a proxy when people take their vacations. Note that Bouman and Jacobsen (2002) do not link time-series evidence on outbound travel to stock returns series, but only consider the cross-sectional evidence with respect to vacations. That is, countries with a strong vacation tradition, measured using three different proxies, exhibit the seasonal effect more strongly. Looking at Figure 2, we see that the seasonal pattern in the detrended UK airline travel is closely related to the one in the other variables.

Please insert Table 5 around here.

Table 5 presents our results. Ice cream production in the US (current and one-month lagged) as proxy for depression among investors seems to work very well. In many countries we find a strong and negative relation with stock returns. Detrended UK airline travel works even better. In all countries the sign is negative as expected and in 33 of the 48 stock markets we find that airline travel is significantly correlated with stock returns. Thus, it seems that any variable with a strong summer/winter pattern 'explains' the stock market seasonality. Without any further support this means that the suggested relations could just be data-driven inference based on spurious correlations.

[20] As an example, higher ice cream sales are positively correlated with the murder rate in the US.
[21] Data from Washington Agricultural Statistics Service.
[22] These (seasonally unadjusted) data are taken from National Statistics Data, source: www.bized.ac.uk.

3. Conclusion

Our analysis shows that it is simply not enough to link weather variables directly to stock returns on the assumption, or using psychological studies, that weather affects mood and therefore affects stock returns. While we find strong evidence on a summer/winter seasonality in stock returns, we find that it is premature to conclude that this effect is caused by weather induced mood changes of investors. We show that while the empirical tests do not conclusively reject probable causes like investors mood changes due to temperature variation or investors collectively suffering from a seasonal affective disorder, these tests do not confirm them either. Unfortunately these causes are plausible but no more than that. In fact the same might be said for investors responding to an old market wisdom creating a self fulfilling prophecy, changing risk aversion due to vacation behavior of investors, seasonal differences in analysts' forecasts or even ice cream production or airline travel for that matter. The main problem is that lots of things are correlated with the seasons and it is hard to distinguish among them when trying to 'explain' seasonal patterns in stock returns. As in many other cases also the significant correlation between weather induced mood shifts and stock returns does not mean this relation is one of causation. Without any further support this means that the suggested relations could just be data-driven inference based on spurious correlations.

Our results do indicate that if one assumes that investors simply adhere to old market wisdom, there is no evidence that investors do suffer from SAD or temperature variation. Or the other way around, if one assumes that investors suffer from temperature variation, they do not seem to be affected by SAD or trading on old market wisdom. Depending on one's believes one might favor one explanation over the other, although we do report some evidence that modeling the seasonality as a SAD effect leaves some predictable seasonality left. Furthermore, our cross-sectional analysis suggests that the SAD and temperature arguments are not robust with respect the countries' proximity to the equator, although these results are not conclusive.

What we have so far are stock returns with a strong seasonal effect. The important question remains what causes this effect. Interesting in this respect is the recent evidence in Kamstra, Kramer and Levi (2003b). This evidence suggests that a collective change of risk aversion by investors might cause this seasonality. Although their empirical evidence allows for many alternative causes of changing risk aversion Kamstra, Kramer and Levi (2003b) choose to attribute this change to SAD. In this respect their study suffers from the same problem as Kamstra, Kramer and Levi (2003a): it fails to substantiate the claim that it is SAD and SAD alone causing this change in risk aversion. In fact, the evidence in Parker and Tavasolli (2000) suggests that sunlight changes have exactly the opposite effects (people in sad moods become risk seeking and people in good moods become more risk averse). This would reject the conclusion that SAD is responsible for the change in risk aversion.

Future research might be able to answer the question whether it is indeed the weather or a change in risk aversion causing this seasonal anomaly, whatever the cause of the change in risk aversion might be. However, until we have any further conclusive empirical or psychological evidence on what causes this effect we find that for future research it is probably most convenient to model the seasonal effect using a simple seasonal dummy. This has the advantage that one does not need temperature data and also that one does not incorrectly assume that it is a specific cause that is responsible for this seasonality.

With respect to the link between weather and investor behavior it would be more convincing if future research could establish a more direct link that weather influences investors' buy and hold decisions. For that, one might to analyze for example account data from individual investors, as is done in studies by Goetzmann and Zhu (2002) and Theissen (2003). However, these studies do not find any evidence of a link between weather (cloud cover and temperature, respectively) and investment decisions. This, together with our results using aggregate data, enables us to conclude that at the moment there is little conclusive empirical evidence to believe that weather induced mood changes of investors moves stock prices.

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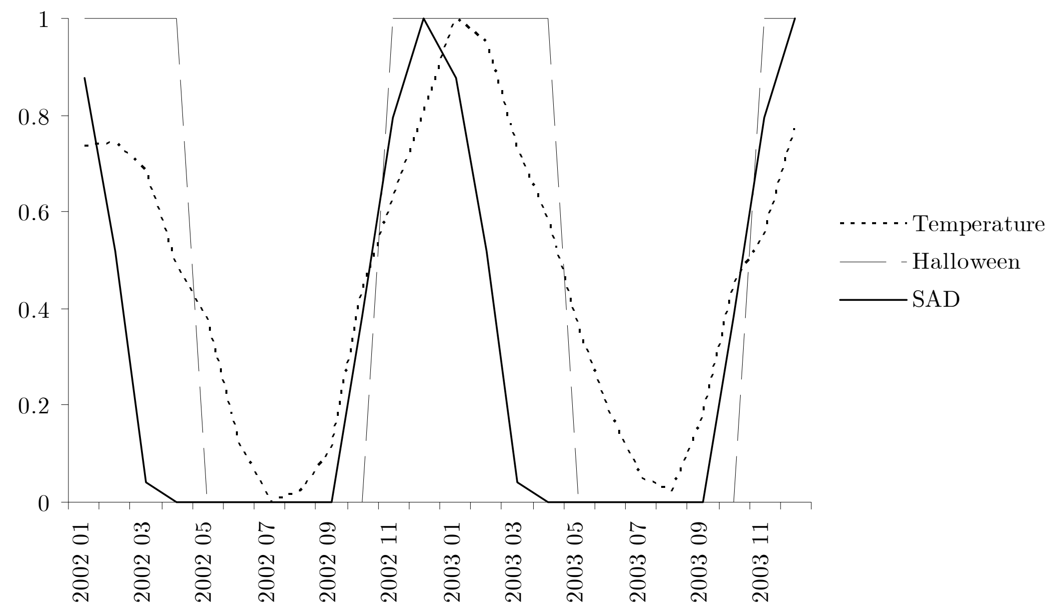

Figure 1. Near multi-collinearity in US temperature, SAD and Halloween variables over the period 2002:01-2003:12.

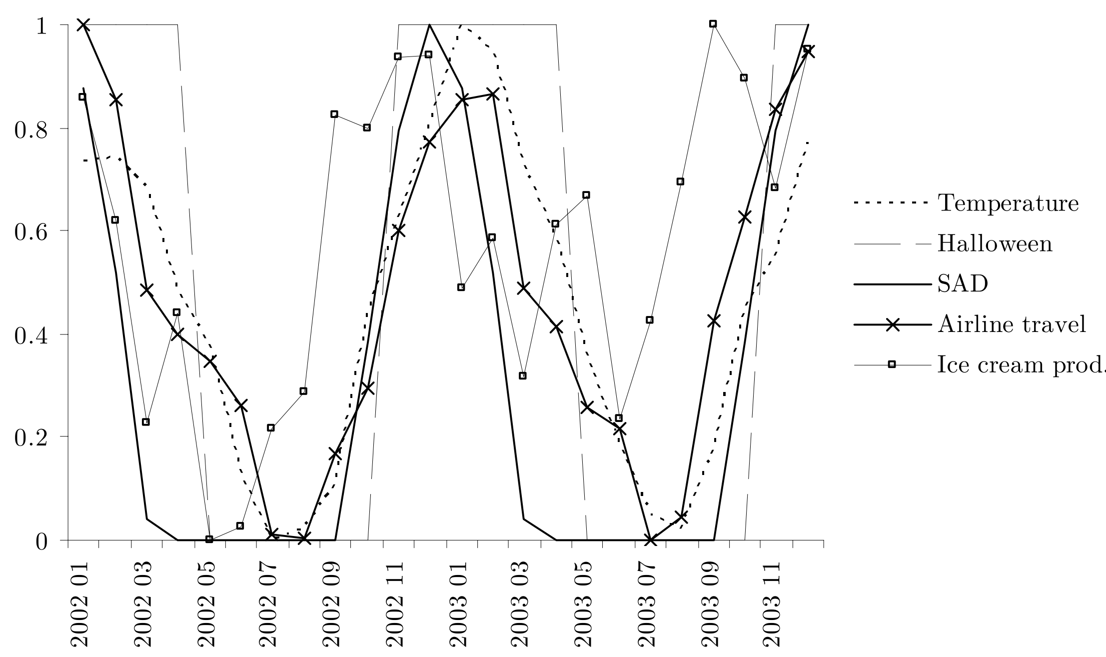

Figure 2. Near multi-collinearity in US temperature, SAD, Halloween, airline travel and ice cream production variables over the period 2002:01-2003:12.

Table 1. Summary results on value weighted MSCI re-investment indices and on the temperature for several countries.

Country	*Latitude*	*Starting date*	Stock Market Returns *Mean (in %)*	*Std.Dev. (in %)*	Temperature *Mean*	*Std. Dev.*
Australia	33°85'S	1970:01	1.00	6.20	18.02	3.83
Austria	48°25'N	1970:01	0.80	5.46	10.25	7.39
Belgium	50°80'N	1970:01	1.10	5.25	10.24	5.62
Canada	43°41'N	1970:01	0.97	5.07	8.74	9.61
Denmark	55°68'N	1970:01	0.86	5.15	8.69	6.26
France	4896'N	1970:01	1.10	6.31	10.81	5.94
Germany	50°05'N	1970:01	0.79	5.91	9.07	6.95
Hong Kong	22°30'N	1970:01	1.89	10.54	23.05	4.55
Italy	45°27'N	1970:01	1.06	7.34	12.75	7.75
Japan	35°41'N	1970:01	0.75	5.43	16.06	7.41
Netherlands	52°10'N	1970:01	0.98	4.77	9.74	5.54
Norway	60°20'N	1970:01	1.33	7.37	4.32	8.08
Singapore	11°8'N	1970:01	1.08	8.30	27.13	0.94
Spain	41°28'N	1970:01	1.14	6.29	14.29	6.65
Sweden	59°65'N	1970:01	1.47	6.87	6.06	7.58
Switzerland	47°38'N	1970:01	0.82	5.33	9.02	6.57
UK	51°15'N	1970:01	1.18	6.29	10.11	4.67
US	40°78'N	1970:01	0.97	4.67	8.75	9.34
Argentina	34°58'S	1988:01	9.13	37.30	17.81	4.79
Brazil	23°50'S	1988:01	3.01	16.49	20.81	2.96
Chile	34°10'S	1988:01	2.58	7.23	14.52	4.53
China	31°16'N	1993:01	-0.24	11.90	16.15	8.32
Colombia	4°36'N	1993:01	2.29	8.86	13.35	0.58
Czech rep.	50°10'N	1995:01	1.09	8.55	8.89	7.15
Egypt	30°13'N	1995:01	1.74	8.87	19.63	4.77
Finland	60°31'N	1988:01	1.80	10.09	4.84	8.45
Greece	37°96'N	1988:01	1.93	10.88	18.29	6.58
Hungary	47°51'N	1995:01	2.58	11.16	10.71	8.03
India	19°10'N	1993:01	1.51	8.68	27.60	1.74
Indonesia	6°11'S	1988:01	2.22	14.36	27.43	0.68
Ireland	53°22'N	1988:01	0.79	6.45	9.67	3.76
Israel	32°60'N	1993:01	1.08	7.38	19.74	5.19
Jordan	31°57'N	1988:01	0.82	4.41	17.42	6.83
Korea	37°34'N	1988:01	1.07	10.37	12.27	9.79
Malaysia	3°70'N	1988:01	1.12	8.77	26.98	0.83
Mexico	19°83'N	1988:01	2.95	8.95	26.47	1.76
Morocco	33°35'N	1995:01	0.97	4.86	17.58	3.67
New Zealand	41°17'S	1988:01	0.69	6.28	12.12	3.35
Pakistan	31°35'N	1993:01	1.58	10.99	23.71	7.26
Philippines	14°35'N	1988:01	1.14	9.29	28.11	1.24
Poland	52°28'N	1993:01	3.04	16.48	8.28	8.23
Portugal	28°43'N	1988:01	0.65	6.47	26.84	1.34
Russia	55°83'N	1995:01	3.50	19.84	5.28	9.60
South Africa	26°13'S	1993:01	1.37	6.60	15.64	3.52
Sri Lanka	6°90'N	1993:01	1.38	10.88	27.58	0.75
Thailand	13°73'N	1988:01	1.57	11.55	28.47	1.48
Turkey	40°96'N	1988:01	6.10	17.80	14.43	6.56
Venezuela	10°50'N	1993:01	4.06	14.37	26.21	1.28

Notes:
1. Ending date for all series is 2004:05.
2. The mean and standard deviation of the temperature is measured in degrees Celsius (°C).

Table 2. Results of regressions using one variable only: respectively, the temperature, the Halloween and the SAD variable; ordered on latitude.

Country	*Latitude*	*Starting date*	Temperature variable *Coeff.*	Temperature variable *t-stat.*	Halloween variable *Coeff.*	Halloween variable *t-stat.*	SAD variable *Coeff.*	SAD variable *t-stat.*
Finland	60°31'N	1988:01	-0.19	**-2.11**	2.54	**1.77**	0.42	1.34
Norway	60°20'N	1970:01	-0.09	**-1.98**	1.63	**2.26**	0.17	1.18
Sweden	59°65'N	1970:01	-0.13	**-2.96**	2.09	**3.12**	0.41	**2.90**
Russia	55°83'N	1995:01	-0.18	-0.96	5.20	1.40	0.59	0.58
Denmark	55°68'N	1970:01	-0.07	**-1.73**	0.86	**1.70**	0.28	**2.18**
Ireland	53°22'N	1988:01	-0.38	**-2.84**	2.27	**2.49**	0.64	**2.45**
Poland	52°28'N	1993:01	-0.08	-0.46	2.32	0.82	0.64	0.82
Netherlands	52°10'N	1970:01	-0.14	**-3.29**	1.66	**3.58**	0.32	**2.51**
UK	51°15'N	1970:01	-0.16	**-2.59**	1.83	**2.99**	0.37	**1.85**
Belgium	50°80'N	1970:01	-0.18	**-3.55**	1.90	**3.74**	0.39	**2.46**
Germany	50°05'N	1970:01	-0.10	**-2.28**	1.31	**2.26**	0.32	**1.80**
Czech rep.	50°10'N	1995:01	-0.11	-0.99	1.34	0.83	0.41	0.72
France	48°96'N	1970:01	-0.18	**-3.52**	2.08	**3.39**	0.33	**1.65**
Austria	48°25'N	1970:01	-0.10	**-2.61**	1.78	**3.35**	0.44	**2.42**
Hungary	47°51'N	1995:01	-0.28	**-1.84**	3.22	1.55	1.50	**1.69**
Switzerland	47°38'N	1970:01	-0.10	**-2.34**	1.00	**1.92**	0.42	**2.35**
Italy	45°27'N	1970:01	-0.15	**-3.14**	2.45	**3.43**	0.76	**2.53**
Canada	43°41'N	1970:01	-0.05	**-1.83**	1.01	**2.03**	0.54	**2.64**
Spain	41°28'N	1970:01	-0.15	**-2.99**	1.74	**2.83**	0.53	**1.90**
Turkey	40°96'N	1988:01	-0.35	**-1.92**	5.02	**2.00**	2.79	**2.15**
US	40°78'N	1970:01	-0.05	**-1.85**	0.80	**1.74**	0.37	**1.79**
Greece	37°96'N	1988:01	-0.12	-1.03	2.41	1.56	0.20	0.29
Korea	37°34'N	1988:01	-0.12	-1.43	1.87	1.27	1.53	**1.79**
Japan	35°41'N	1970:01	-0.12	**-3.43**	1.73	**3.28**	0.56	**1.90**
Morocco	33°35'N	1995:01	-0.30	**-2.04**	1.45	1.60	0.47	0.73
Israel	32°60'N	1993:01	-0.07	-0.49	0.74	0.58	0.37	0.47
Jordan	31°57'N	1988:01	-0.10	**-2.06**	0.82	1.30	1.01	**2.54**
Pakistan	31°35'N	1993:01	-0.20	-1.43	1.46	0.77	3.06	**1.66**
China	31°16'N	1993:01	0.04	0.27	-0.52	-0.25	0.97	0.76
Egypt	30°13'N	1995:01	-0.34	-1.56	4.04	**2.50**	3.34	**2.21**
Portugal	28°43'N	1988:01	-1.15	**-2.50**	1.26	1.37	0.91	**2.05**
Hong Kong	22°30'N	1970:01	-0.20	-1.48	0.80	0.77	0.96	0.85
Mexico	19°83'N	1988:01	-1.34	**-2.98**	1.35	1.06	1.25	0.83
India	19°10'N	1993:01	-8.38	-1.25	3.46	**1.70**	5.78	**1.85**
Philippines	14°35'N	1988:01	0.29	0.42	1.90	1.44	4.82	**2.06**
Thailand	13°73'N	1988:01	-1.29	**-2.11**	3.12	**1.90**	7.28	**2.42**
Venezuela	10°50'N	1993:01	-0.52	-0.47	0.58	0.24	1.14	0.17
Sri Lanka	6°90'N	1993:01	1.46	0.90	-1.28	-0.68	-0.84	-0.12
Colombia	4°36'N	1993:01	0.88	0.60	3.59	**2.43**	29.85	**2.82**
Malaysia	3°70'N	1988:01	-0.85	-0.76	1.98	1.60	22.23	**1.75**
Singapore	1°18'N	1970:01	-0.84	**-1.70**	1.68	**2.06**	-8.10	-0.91
Indonesia	6°11'S	1988:01	-1.05	**-2.51**	3.00	**2.05**	5.62	**3.11**
Brazil	23°50'S	1988:01	1.30	**1.97**	6.35	**2.76**	-3.44	**-1.79**
South Africa	26°13'S	1993:01	0.39	**2.38**	2.47	**2.22**	-1.70	**-1.67**
Australia	33°85'S	1970:01	0.14	**1.78**	1.24	**2.04**	-0.52	**-1.78**
Chile	34°10'S	1988:01	0.21	1.50	2.14	**2.10**	-9.57	**-2.37**
Argentina	34°58'S	1988:01	-0.16	-0.26	1.61	0.30	0.46	0.17
New Zealand	41°17'S	1988:01	0.11	0.93	1.08	1.20	-0.06	-0.17

Notes:
1. Ending date for all series is 2004:05.
2 The reported t-statistics are based on heteroscedasticity consistent standard errors. Bold numbers indicate statistical significance at the 5% level (one-sided test).
3. The coefficients are scaled by a factor 100.

Table 3. Summary of the results of regressions of returns on a seasonal variable and two orthogonal residual variables. The results are obtained from estimating:

$$r_t = \alpha + \beta_1 May_t + \beta_2 \hat{\varepsilon}^{temp}_{\{may\},t} + \beta_3 \hat{\varepsilon}^{SAD}_{\{may,temp\},t} + \varepsilon_t ,$$

where the unexplained residuals $\hat{\varepsilon}^{temp}_{\{may\},t}$ and $\hat{\varepsilon}^{SAD}_{\{may,temp\},t}$ are obtained from a temperature and SAD regression: $Temp_t = \mu + \delta May_t + \varepsilon^{temp}_{\{may\},t}$, and $SAD_t = \eta + \gamma_1 May_t + \gamma_2 Temp_t + \varepsilon^{SAD}_{\{may,temp\},t}$, respectively. The other combinations of variables are obtained accordingly. The number of "correct" ("wrong") signs indicates the number of countries with a corresponding statistically significant coefficient with the (opposite) sign as expected as described in Section 1. The Wald test tests simultaneously if all partial slope coefficients are equal to zero. The Wald test is a χ^2 test with 48 degrees of freedom.

Explanatory Variables	Number of "correct" signs	Number of "wrong" signs	Wald test	p-value
May_t	32	0	205.2857	**(0.0000)**
$\hat{\varepsilon}^{temp}_{\{may\},t}$	5	0	63.7027	(0.0641)
$\hat{\varepsilon}^{SAD}_{\{may,temp\},t}$	7	0	43.0805	(0.6742)
May_t	28	0	205.8821	**(0.0000)**
$\hat{\varepsilon}^{temp}_{\{may,SAD\},t}$	4	1	57.6233	(0.1610)
$\hat{\varepsilon}^{SAD}_{\{may\},t}$	3	0	48.7076	(0.4464)
$Temp_t$	25	3	217.6985	**(0.0000)**
$\hat{\varepsilon}^{may}_{\{temp\},t}$	6	0	51.6976	(0.3315)
$\hat{\varepsilon}^{SAD}_{\{temp,may\},t}$	6	0	43.0805	(0.6742)
$Temp_t$	26	3	217.7948	**(0.0000)**
$\hat{\varepsilon}^{may}_{\{temp,SAD\},t}$	4	1	43.4234	(0.6995)
$\hat{\varepsilon}^{SAD}_{\{temp\},t}$	7	1	51.5606	(0.3363)
SAD_t	24	1	99.9213	**(0.0000)**
$\hat{\varepsilon}^{may}_{\{SAD\},t}$	12	0	66.4486	**(0.0400)**
$\hat{\varepsilon}^{temp}_{\{SAD,may\},t}$	4	2	63.8541	(0.0625)
SAD_t	25	3	99.8085	**(0.0000)**
$\hat{\varepsilon}^{may}_{\{SAD,may\},t}$	4	1	56.8034	(0.1799)
$\hat{\varepsilon}^{temp}_{\{SAD\},t}$	8	1	85.8212	**(0.0007)**

Notes:
1. The reported p-values are based on heteroscedasticity consistent standard errors. Bold numbers indicate statistical significance at the 5% level (two-sided test).

Table 4. Results of using subsamples of regressions using one variable only: respectively, the temperature, the Halloween and the SAD variable; ordered on latitude.

		Temperature variable		Halloween variable		SAD variable	
		1st half	*2nd half*	*1st half*	*2nd half*	*1st half*	*2nd half*
Country	*Latitude*	*Coeff. (t-stat.)*	*Coeff. (t-stat.)*	*Coeff. (t-stat.)*	*Coeff. (t-stat.)*	*Coeff. (t-stat.)*	*Coeff. (t-stat.)*
Norway	60°20'N	0.02	-0.18	0.29	2.97	0.03	0.31
		(0.26)	(**-2.75**)	(0.28)	(**2.99**)	(0.13)	(1.59)
Sweden	59°65'N	-0.11	-0.16	2.25	1.92	0.42	0.40
		(**-2.18**)	(**-2.05**)	(**2.89**)	(**1.76**)	(**2.55**)	(**1.72**)
Denmark	55°68'N	0.01	-0.17	0.26	1.55	0.22	0.35
		(0.13)	(**-2.55**)	(0.18)	(**2.11**)	(1.20)	(**1.88**)
Netherlands	52°10'N	-0.12	-0.16	1.84	1.48	0.38	0.27
		(**-2.69**)	(**-2.21**)	(**3.36**)	(**1.97**)	(**2.30**)	(1.35)
UK	51°15'N	-0.21	-0.09	2.67	0.98	0.58	0.16
		(**-2.32**)	(-1.15)	(**2.76**)	(1.32)	(**1.69**)	(0.77)
Belgium	50°80'N	-0.19	-0.17	2.30	1.50	0.59	0.18
		(**-3.21**)	(**-2.01**)	(**3.85**)	(**1.81**)	(**2.91**)	(0.74)
Germany	50°05'N	-0.05	-0.14	1.19	1.43	0.27	0.38
		(-1.16)	(**-2.02**)	(**1.83**)	(1.49)	(1.30)	(1.28)
France	48°96'N	-0.17	-0.19	2.16	2.00	0.40	0.25
		(**-2.54**)	(**-2.45**)	(**2.59**)	(**2.21**)	(1.44)	(0.89)
Austria	48°25'N	-0.04	-0.16	1.15	2.41	0.12	0.79
		(-1.17)	(**-2.42**)	(**2.16**)	(**2.63**)	(0.65)	(**2.46**)
Switzerland	47°38'N	-0.09	-0.11	1.07	0.94	0.67	0.16
		(**-1.98**)	(**-1.58**)	(**1.69**)	(1.13)	(**2.84**)	(0.62)
Italy	45°27'N	-0.16	-0.15	2.16	2.73	0.80	0.71
		(**-2.23**)	(**-2.17**)	(**2.11**)	(**2.73**)	(**1.85**)	(**1.70**)
Canada	43°41'N	-0.04	-0.06	1.28	0.73	0.77	0.30
		(-1.15)	(**-1.46**)	(**1.74**)	(1.10)	(**2.47**)	(1.16)
Spain	41°28'N	-0.14	-0.17	1.66	1.83	0.36	0.70
		(**-2.37**)	(**-1.99**)	(**2.16**)	(**1.90**)	(0.95)	(**1.71**)
US	40°78'N	-0.04	-0.05	0.92	0.68	0.52	0.22
		(-1.19)	(**-1.44**)	(1.46)	(1.01)	(**1.80**)	(0.73)
Japan	35°41'N	-0.14	-0.10	1.92	1.52	0.88	0.23
		(**-3.25**)	(**-1.69**)	(**2.96**)	(**1.84**)	(**2.38**)	(0.52)
Hong Kong	22°30'N	-2.47	-0.19	0.95	0.62	0.76	0.93
		(-0.88)	(-1.40)	(0.57)	(0.51)	(0.26)	(0.79)
Singapore	1°18'N	-0.50	-1.01	1.26	2.08	-16.79	0.97
		(-0.64)	(-1.70)	(1.01)	(**2.02**)	(-1.31)	(0.08)
Australia	33°85'S	0.15	0.14	0.88	1.60	-0.68	-0.36
		(1.25)	(1.27)	(0.95)	(**2.04**)	(-1.42)	(-1.07)

Notes:
1. 1st half refers to the subperiod 1970:1-1987:3 and the 2nd half to 1987:4-2004:5.
2 The reported t-statistics are based on heteroscedasticity consistent standard errors. Bold numbers indicate statistical significance at the 5% level (one-sided test).
3. The coefficients are scaled by a factor 100.

Table 5. Results of regressions using respectively, US ice production and UK airline travel.

Country	*Starting date*	Ice production variable		Lagged ice production variable		Airline travel variable	
		Coeff.	*t-stat.*	*Coeff.*	*t-stat.*	*Coeff.*	*t-stat.*
Australia	1970:01	0.12	0.13	-1.11	-1.15	-1.42	**-2.75**
Austria	1970:01	-1.32	-1.40	-2.50	**-2.65**	-1.31	**-2.73**
Belgium	1970:01	-0.51	-0.66	-1.35	-1.58	-1.43	**-3.29**
Canada	1970:01	-0.34	-0.42	-0.80	-0.89	-0.66	-1.53
Denmark	1970:01	-0.56	-0.67	0.05	0.06	-0.68	-1.46
France	1970:01	-0.67	-0.73	-1.65	-1.60	-1.54	**-3.05**
Germany	1970:01	-0.38	-0.40	-1.25	-1.24	-1.43	**-2.78**
Hong Kong	1970:01	-3.68	**-2.21**	-2.33	-1.38	-1.20	-1.55
Italy	1970:01	-1.69	-1.49	-1.61	-1.52	-1.93	**-3.19**
Japan	1970:01	-1.19	-1.36	-1.84	**-2.09**	-1.19	**-2.53**
Netherlands	1970:01	-0.80	-1.10	-1.19	-1.50	-1.39	**-3.55**
Norway	1970:01	-0.69	-0.65	-1.97	**-1.67**	-0.72	-1.17
Singapore	1970:01	-4.27	**-3.06**	-3.14	**-2.29**	-1.15	**-1.86**
Spain	1970:01	-1.58	-1.58	-1.57	-1.51	-1.75	**-3.34**
Sweden	1970:01	-1.37	-1.33	-2.04	**-1.94**	-2.25	**-3.74**
Switzerland	1970:01	0.03	0.03	-0.69	-0.73	-1.13	**-2.46**
UK	1970:01	-1.09	-1.20	-1.37	-1.28	-1.36	**-3.39**
US	1970:01	0.18	0.25	-0.49	-0.65	-0.99	**-2.54**
Argentina	1988:01	-11.08	-1.63	-14.34	**-1.70**	-9.90	**-3.32**
Brazil	1988:01	-5.53	**-1.84**	-6.40	**-1.82**	-4.90	**-3.32**
Chile	1988:01	-5.40	**-3.49**	-5.36	**-3.49**	-2.56	**-3.29**
China	1993:01	1.18	0.37	0.22	0.08	-0.02	-0.01
Colombia	1993:01	-6.80	**-3.57**	-4.26	**-1.99**	-2.28	**-2.04**
Czech rep.	1995:01	-2.44	-1.03	-3.54	-1.48	-1.26	-1.03
Egypt	1995:01	-1.94	-1.01	-3.09	-1.34	-3.79	**-3.13**
Finland	1988:01	-1.97	-0.89	-0.87	-0.42	-1.30	-1.21
Greece	1988:01	0.41	0.17	-1.00	-0.51	-1.83	**-1.64**
Hungary	1995:01	-1.00	-0.34	-3.53	-1.10	-4.90	**-2.38**
India	1993:01	-5.37	**-1.81**	-7.18	**-2.46**	-3.24	**-2.33**
Indonesia	1988:01	-1.85	-1.05	-5.20	**-2.96**	-2.21	**-1.94**
Ireland	1988:01	-2.44	**-1.98**	-1.27	-0.97	-1.70	**-2.31**
Israel	1993:01	-1.52	-0.87	-1.35	-0.73	-0.35	-0.37
Jordan	1988:01	-2.93	**-3.59**	-2.85	**-3.44**	-1.21	**-2.86**
Korea	1988:01	-1.75	-0.76	-2.53	-1.23	-0.92	-0.82
Malaysia	1988:01	-6.48	**-3.76**	-5.68	**-2.92**	-2.44	**-2.47**
Mexico	1988:01	-2.84	-1.58	-3.40	**-1.70**	-2.12	**-2.07**
Morocco	1995:01	2.46	**2.30**	0.61	0.52	-1.91	**-3.05**
New Zealand	1988:01	0.06	0.05	-0.90	-0.68	-0.68	-1.03
Pakistan	1993:01	-4.65	-1.45	-5.06	**-1.76**	-2.27	**-1.71**
Philippines	1988:01	-4.32	**-2.21**	-3.68	**-1.81**	-3.45	**-3.56**
Poland	1993:01	-5.51	**-1.74**	-3.88	-1.31	-6.02	**-3.16**
Portugal	1988:01	-1.84	-1.40	-0.71	-0.51	-1.35	**-2.05**
Russia	1995:01	-2.92	-0.49	-8.01	-1.36	-3.66	-1.17
South Africa	1993:01	-2.57	-1.51	-2.36	-1.34	-1.46	-1.48
Sri Lanka	1993:01	-3.66	-1.17	-3.51	-1.35	-0.98	-0.71
Thailand	1988:01	-7.04	**-2.89**	-5.78	**-2.34**	-2.67	**-1.99**
Turkey	1988:01	-8.44	**-2.21**	-6.31	**-1.67**	-4.02	**-2.31**
Venezuela	1993:01	-1.82	-0.55	-1.11	-0.29	-2.33	-1.27

Notes:
1. Ending date for all series is 2004:05.
2. The reported t-statistics are based on heteroscedasticity consistent standard errors. Bold numbers indicate statistical significance at the 5% level (one-sided test).
3. The airline travel is measured in excess of its trend. The coefficients are scaled by a factor 10000.

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