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Is it the weather?

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Abstract

We show that results in the recent strand of the literature, which 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, Mark J., Kramer, Lisa A., Levi, Maurice D., 2003a. Winter blues: A SAD stock market cycle. American Economic Review 93(1), 324–343; Cao, Melanie, Wei, Jason, 2005. Stock market returns: A note on temperature anomaly. Journal of Banking and Finance 29(6), 1559–1573] 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. While 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 as documented by Bouman and Jacobsen [Bouman, Sven, Jacobsen, Ben, 2002. The Halloween indicator, Sell in May and go away: Another puzzle. American Economic Review, 92(5), 1618–1635], there is little evidence in favor of a SAD or temperature explanation. In fact, we find that a simple winter/summer dummy best describes this seasonality. Our results suggest that without any further evidence the correlation between weather-related variables and stock returns might be spurious and the conclusion that weather affects stock returns through mood changes of investors is premature.

JEL classification: G10; G12

Keywords: Stock market seasonality; Sell in May; Seasonal affective disorder; Temperature effect; Spurious correlations

Starting with the seminal paper of Saunders (1993), a new and interesting strand of research has evolved which investigates the possible impact of weather variables on investor behavior. Saunders (1993) and subsequently Hirshleifer and Shumway (2003) find a strong relation between cloud cover and stock returns. Kamstra et al. (2000) report lower stock returns after weekends with daylight savings time changes. Dichev and Janes (2003) and Yuan et al. (2006) relate stock returns to lunar phases. More recently, Kamstra et al. (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 (2005) 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 et al., 2000, 2003a) or misattribution (Saunders, 1993; 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.

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That this might be the case for the studies using cloud cover is illustrated in recent work of Goetzmann and Zhu (2005). 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 et al. (2003a) and Cao and Wei (2005). 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 et al. (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 months.

Finally, Cao and Wei (2005) hypothesize that temperature influences stock market returns as some psychological studies show that extreme weather changes human behavior. Cao and Wei (2005) 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 et al. (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 et al. (2003a), that the SAD variable and stock returns are highly correlated, and similar to Cao and Wei (2005) 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 et al. (2003a) and Cao and Wei (2005).

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. Non-nested tests show that a model specification with a Sell in May dummy is superior to specifications with temperature or SAD as explanatory variable. We further show that cross-sectional evidence across countries suggests that the SAD and temperature arguments are not robust with respect the countries' proximity to the equator. Overall, a specification with a simple winter/summer dummy variable seems superior. 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 stock returns.

Our findings are robust to the inclusion of known anomalies such as the January and October effect, the daylight savings time changes effect, and the inclusion of the country-specific earnings price ratios and the NBER recession variable. Moreover, our results are robust after adjusting for cross-country correlation, and we additionally estimated all versions with robust GMM and maximum likelihood with GARCH effects. With the exception of some minor quantitative changes, overall the results are very similar to the OLS results.

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 et al., 2003b; Diao and Levi, 2004; Garrett et al., 2005) 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

[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.

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

using a simple seasonal dummy until we have further evidence on the probable cause of this seasonality. First of all, models using the simple Sell in May dummy dominate the alternative weather specifications in all our tests. Secondly, one does not need temperature data or complicated trigonometric formulas. Thirdly, and most importantly, one does not have 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. The robustness checks of the results are presented in Section 3, and Section 4 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). The anomaly is examined by including a simple dummy (referred to as the Sell in May dummy or Halloween dummy) in the regression equations. 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 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 et al. (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 et al. (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 et al. (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 (2005) 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.

Cao and Wei (2005) 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

[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 (2007) suggest that the inclusion of this dummy might lead to spurious significant results (see also footnote 15). In addition, the fall dummy might pick up effects completely unrelated to SAD.

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

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 et al. (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 and find that stock returns are significantly negatively related to temperature. The control variables used are similar to the ones used in Kamstra et al. (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. Surprisingly, both studies do not include a Halloween dummy in their analysis.

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 (2005) 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 also have a noticeable effect on human behavior and thus stock returns remains questionable. A recent study, Theissen (2007), 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 et al. (2003a) suggest, have recently been criticized by Kelly and Meschke (2007). 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 Tavassoli (2000) find the opposite behavior to changes in sunlight than Kamstra et al. (2003a). Parker and Tavassoli (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 Tavassoli (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 (2005) and Kamstra et al. (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 (2005). However, Kamstra et al. (2003a) estimate a regression with a temperature and SAD variable jointly, so near-perfect multicollinearity could be a problem. Cao and Wei (2005), 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 (2005) 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 (2005) and Kamstra et al. (2003a) (only) use daily data remains unclear. It is well known, that daily data are considerably noisier than for instance monthly data which is also noted by Garrett et al. (2005). Daily data are for instance hampered by non-synchronous trading problems, strong time-varying volatility, skewness

[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 Tavassoli (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.

[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.

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 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?

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 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 (NCDC) and Carbon Dioxide Information Analysis Center, is created from 15 source data sets.[10] Following Cao and Wei (2005), 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. For the developed countries, we have around 400 observations for each country.[11] For the remaining 30 countries, we have between 120 and 200 observations for each country. Occasionally some temperature observations were missing from the sample (some observations were manually removed 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.

We employ a number of control variables in our regressions.[12] In our main model, we include the following three variables: the return on a world stock index, a January dummy and a NBER recession dummy. The world index return is included to remove effects of global economic change from the country index movements, and to take into account cross-country correlation. The source of this data is MSCI Barra. The series are corrected for a seasonal trend to prevent multicollinearity. The January dummy is included in all regressions to correct for the January anomaly, which is often associated to a tax-loss selling effect. Finally, we include the NBER recession dummy. This dummy is equal to one during periods identified by NBER as recessions and zero otherwise. The NBER recession dummy represents the changes in macroeconomic conditions. Andreou et al. (2001) found that stock returns tend to increase before a recession, then decline some weeks prior to the trough date. This could imply that stock returns are seasonal partly because of recession seasonality, or more generally, seasonality in changing macroeconomic conditions. To examine this possibility, we include the NBER variable in all specifications. We find that especially for Austria, Denmark, Hong

[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 database 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.

[12] While results here include all control variables, we obtain similar results if we estimate simple linear regression models without any control variables.

Kong, Italy, Japan, Norway and Switzerland, the statistical significance of the estimated coefficients corresponding to the NBER dummy is strong. For these countries, there is a significant contemporaneous relation between recessions and stock market returns.

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:

$$r_r = \alpha + \beta_1 S_t + \beta_2 r_t^W + \beta_3 \mathrm{JAN}_t + \beta_4 \mathrm{NBER}_t + \varepsilon_t,$$

where S_t is a seasonal variable. This variable is a dummy variable in the case of the Sell in May effect (May_t). 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 (Temp_t) of the corresponding country. Finally, to test the SAD effect in our data, S_t is the country-specific SAD variable reflecting the length of the night in the fall and winter relative to the mean annual length of twelve hours (see Kamstra et al., 2003a), denoted by SAD_t.[13] Finally, we include three control variables which were selected based on extensive model testing.[14] Control variable r_t^W is the return on the MSCI world index. JAN_t is a January dummy to take into account typically higher average returns in the month January; and NBER_t is a recession dummy which is equal to one during periods identified by NBER as recessions and zero otherwise, reflecting changes in macroeconomic conditions.

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.[15] For each seasonal variable we test whether the corresponding coefficient is significantly different from zero. The results are presented in Table 1. In addition, we report the latitude of the location of the (main) stock exchange of each country in this table.

In line with Cao and Wei (2005), most estimated coefficients of the temperature variable are negative. We find a negative and significant (at the 5% significance level) temperature effect present in 22 countries.[16] In two countries, the effect is significantly positive. Consistent with Bouman and Jacobsen (2002), the Halloween effect seems strong: we find it significantly present in 27 countries. And finally, confirming the results of Kamstra et al. (2003a), we find that the SAD variable is also significant in many countries.[17] In 15 countries, it is significant with a positive sign, but in four countries – all on the southern Hemisphere – 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 tests seems affected by the number of observations.

The results in Table 1 answer the first question we posed in the beginning of this section: Do we still observe a

[13] In formula:

$$\mathrm{SAD}_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise,} \end{cases}$$

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

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

[14] To arrive at our basic model, we adopt a structured variable selection approach. Starting with a model including only a constant term and the temperature variable as explanatory variables, we include other possible relevant variables. The selection criteria we use are the adjusted R^2 and the Akaike information criterion (AIC); see Greene (2002, pp. 159–160) for more details on these criterions. We repeat this procedure for each country, and select the preferred model by selecting the one that dominates. We repeat this procedure for the models with the Sell in May dummy and SAD variable. The results are consistent among the models with different seasonal variables and strongly indicate models including a seasonal variable, a world return index, a January and the NBER dummy.

[15] In our regressions analyzing the asymmetry in SAD, we find significant temperature dummies in 26 countries (three negative), a significant Halloween effect in 28 countries and a significant SAD effect in 28 countries (five negative). 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 (2007) 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 spurious statistical significance. Kelly and Meschke (2007) conclude that the negative fall coefficient in Kamstra et al. (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 analyzes 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.

[16] Note that occasionally a temperature observation is missing. We also estimated a version in which the missing observations were replaced by the average of the preceding and following observation, and in case of multiple consecutive missing observations, the temperature of the preceding year was entered. This resulted in very similar and qualitative identical results.

[17] Following Kamstra et al. (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.

Table 1
Results of regressions using only one 'weather variable' in $r_r = \alpha + \beta_1 S_t + \beta_2 r_t^W + \beta_3 \mathrm{JAN}_t + \beta_4 \mathrm{NBER}_t + \varepsilon_t$

Country	Latitude	Starting date	Temperature variable		Halloween variable		SAD variable	
			Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Finland	60°31′N	1988:01	−0.19	*−2.10*	2.66	*1.85*	0.38	1.13
Norway	60°20′N	1970:01	−0.05	−1.09	1.06	1.54	−0.12	−0.83
Sweden	59°65′N	1970:01	−0.11	*−2.38*	1.86	*2.90*	0.29	*1.98*
Russia	55°83′N	1995:01	−0.31	−1.57	6.61	*1.82*	0.29	*1.98*
Denmark	55°68′N	1970:01	−0.05	−1.20	0.69	*1.83*	0.22	1.53
Ireland	53°22′N	1988:01	−0.39	*−2.90*	2.35	*2.61*	0.64	*2.44*
Poland	52°28′N	1993:01	0.01	0.06	1.64	0.57	0.33	0.41
Netherlands	52°10′N	1970:01	−0.12	*−3.09*	1.53	*3.93*	0.18	1.63
UK	51°15′N	1970:01	−0.10	*−1.78*	1.53	*3.01*	0.10	0.66
Belgium	50°80′N	1970:01	−0.16	*−3.07*	1.78	*3.67*	0.25	1.55
Germany	50°05′N	1970:01	−0.11	*−2.49*	1.39	*2.52*	0.31	*1.72*
Czech rep.	50°10′N	1995:01	−0.15	−1.23	1.59	0.97	0.60	0.92
France	48°96′N	1970:01	−0.17	*−3.27*	1.98	*3.47*	0.13	0.73
Austria	48°25′N	1970:01	−0.11	*−2.75*	1.93	*3.65*	0.48	*2.59*
Hungary	47°51′N	1995:01	−0.24	*−2.05*	2.41	1.44	1.21	*1.71*
Switzerland	47°38′N	1970:01	−0.08	*−2.00*	0.88	*1.89*	0.29	*1.80*
Italy	45°27′N	1970:01	−0.10	*−2.24*	1.94	*2.82*	0.28	0.96
Canada	43°41′N	1970:01	−0.05	*−2.49*	0.99	*2.62*	0.46	*2.96*
Spain	41°28′N	1970:01	−0.14	*−2.74*	1.62	*2.74*	0.31	1.08
Turkey	40°96′N	1988:01	−0.30	−1.57	4.83	*1.87*	2.73	*1.89*
US	40°78′N	1970:01	−0.04	*−2.26*	0.77	*2.33*	0.22	1.54
Portugal	38°43′N	1988:01	−0.95	*−2.24*	1.07	1.25	0.61	1.54
Greece	37°96′N	1988:01	−0.06	−0.52	2.24	1.40	−0.37	−0.55
Korea	37°34′N	1988:01	−0.07	−0.89	1.56	1.14	0.94	1.07
Japan	35°41′N	1970:01	−0.13	*−3.82*	1.69	*3.61*	0.32	1.10
Morocco	33°35′N	1995:01	−0.07	−0.42	0.42	0.45	−0.76	−1.34
Israel	32°60′N	1993:01	−0.09	−0.60	0.88	0.71	0.55	0.68
Jordan	31°57′N	1988:01	−0.11	*−2.02*	0.85	1.32	1.09	*2.56*
Pakistan	31°35′N	1993:01	−0.20	−1.31	1.13	0.58	3.27	1.56
China	31°16′N	1993:01	−0.02	−0.14	0.38	0.18	−0.21	−0.15
Egypt	30°13′N	1995:01	−0.14	−0.70	2.79	*1.83*	2.11	1.50
Hong Kong	22°30′N	1970:01	−0.28	*−2.31*	0.40	0.41	1.65	1.58
Mexico	19°83′N	1988:01	−1.48	*−3.19*	2.05	1.60	1.85	1.21
India	19°10′N	1993:01	−9.22	−1.20	2.26	1.48	5.75	1.45
Philippines	14°35′N	1988:01	0.09	0.13	2.41	*1.87*	5.53	*2.03*
Thailand	13°73′N	1988:01	−1.36	*−2.09*	2.92	*1.84*	5.79	*1.83*
Venezuela	10°50′N	1993:01	0.13	0.12	1.24	0.48	5.50	0.77
Sri Lanka	6°90′N	1993:01	1.16	0.70	−0.68	−0.37	2.49	0.33
Colombia	4°36′N	1993:01	1.79	1.26	2.98	*1.98*	22.24	*2.14*
Malaysia	3°70′N	1988:01	−0.98	−0.95	2.43	*1.98*	20.32	*1.68*
Singapore	1°18′N	1970:01	−0.74	−1.61	1.17	1.58	19.00	*1.66*
Indonesia	6°11′S	1988:01	−1.05	*−2.51*	3.51	1.62	−4.78	*−2.44*
Brazil	23°50′S	1988:01	1.46	*2.09*	6.87	*2.98*	−3.31	*−1.74*
South Africa	26°13′S	1993:01	0.44	*3.01*	2.93	*2.97*	−2.24	*−2.10*
Australia	33°85′S	1970:01	0.11	1.51	1.00	*1.88*	−0.17	−0.63
Chile	34°10′S	1988:01	0.19	1.31	2.24	*2.09*	−9.77	*−2.11*
Argentina	34°58′S	1988:01	0.01	0.02	2.95	0.51	−0.58	−0.18
New Zealand	41°17′S	1988:01	0.14	1.05	1.33	1.48	−0.03	−0.07

We include respectively, the temperature, Halloween and SAD variable. Countries are ordered on latitude. Only the estimates and corresponding *t*-statistics of the 'weather variable' are presented here.
Notes:
1. Ending date for all series is 2004:05. Coeff. denotes estimated coefficient; *t*-stat. denotes the corresponding *t*-statistic.
2. The reported *t*-statistics are based on heteroscedasticity consistent standard errors. Italisized numbers indicate statistical significance at the 5% level (one-sided test).
3. The coefficients are scaled by a factor 100.

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

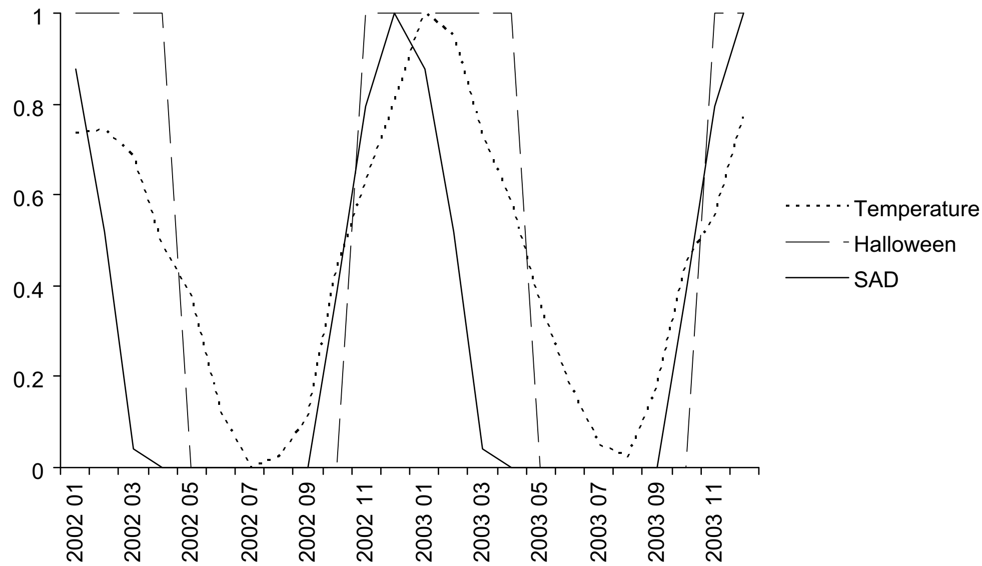

Fig. 1. Near-perfect multicollinearity in US temperature, SAD and Halloween variables over the period 2002:01–2003:12.

we find evidence even if we consider longer horizons and lower frequency data than used in previous studies.[18]

2.3. Testing for the combined effects

Clearly, the obvious way to proceed would be to jointly include all explanatory seasonal variables in one regression and check which of the variables explains the variability in returns best. If one does, nearly all the seasonal variables' coefficients become statistically insignificant.[19] The problem is that these seasonal variables are highly correlated. Consequently, we have a situation of near-perfect multicollinearity. Fig. 1, where we compare the three variables, shows the problem graphically. 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 Fig. 1, we see that the seasonal patterns in the variables are closely related.

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-perfect multicollinearity. This complicates the fundamental problem of choosing between several models.

To overcome this problem, we first 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.[20]

In formula, for each country, we estimate in a first step the following two OLS regressions:[21]

[18] An alternative way to examine what causes the anomaly is to check whether the coefficients are stable over time. If it were 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? Nowadays we are better able and equipped to isolate ourselves from the influence of the weather (for instance, through 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. The main observation is that the effect of temperature tends to increase over time. This suggests that the temperature explanation is not plausible.

[19] This occurs irrespectively from estimation method or model specification. The estimation results are not reported here, but can be obtained from the authors upon request.

[20] 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 that splits the SAD variable in a fall and winter SAD variable did not alter our conclusions.

[21] 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: $\text{Temp}_t = \mu + \delta\text{May}_t + \varepsilon_t^{\text{temp}}$ and $\text{SAD}_t = \eta + \gamma\text{May}_t + \varepsilon_t^{\text{SAD}}$. There are no major differences that alter any of the conclusions using this specification.

$$\mathrm{Temp}_t = \mu + \delta \mathrm{May}_t + \varepsilon^{\mathrm{temp}}_{\{\mathrm{may}\},t}$$
$$\mathrm{SAD}_t = \eta + \gamma_1 \mathrm{May}_t + \gamma_2 \mathrm{Temp}_t + \varepsilon^{\mathrm{SAD}}_{\{\mathrm{may,temp}\},t},$$

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:

$$r_t = \alpha + \beta_1 \mathrm{May}_t + \beta_2 \hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{may}\},t} + \beta_3 \hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{may,temp}\},t} + W'_t\phi + \varepsilon_t,$$

where W_t denotes the vector of common variables and ϕ the corresponding coefficient vector ($W'_t\phi = \phi_1 r^W_t + \phi_2 \mathrm{JAN}_t + \phi_3 \mathrm{NBER}_t$). The unexplained residuals $\hat{\varepsilon}^{\mathrm{temp}}_t$ and $\hat{\varepsilon}^{\mathrm{SAD}}_t$ 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:

$$\mathrm{Temp}_t = \mu + \delta_1 \mathrm{May}_t + \delta_2 \mathrm{SAD}_t + \varepsilon^{\mathrm{temp}}_{\{\mathrm{may,SAD}\},t}$$
$$\mathrm{SAD}_t = \eta + \gamma \mathrm{May}_t + \varepsilon^{\mathrm{SAD}}_{\{\mathrm{may}\},t},$$

and estimate the return equation including the residuals from these equations. A similar approach is employed for the other 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 2 (Panel A) a summary of these results.[22]

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 33 countries (second column, second row of Table 2, Panel A). But assuming a Sell in May effect, the value of additional information from the temperature variable is marginal: only in four 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 six 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 Panel A of Table 2 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 61.37 and 40.74, 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 unexplained seasonality in the data. The practical implication for future research is that, if one lacks temperature data, the easiest way to 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.

An alternative and possibly more powerful way to choose between models is to employ a non-nested test taking into account possible multicollinearity: the *J*-test of Davidson and Mackinnon (1981). This is a powerful test to discriminate one model against another, whereas these models are not necessarily nested. Say, we want to test a model with the Sell in May variable against a model with the SAD variable. In formula:

$$H_0: r_t = \mu + \beta \mathrm{May}_t + W'_t\delta + \varepsilon_t$$
$$H_1: r_t = \eta + \gamma \mathrm{SAD}_t + W'_t\vartheta + \varepsilon_t,$$

where W_t again denotes the vector of common variables in both models. A 'supermodel' including all variables often leads to near-perfect multicollinearity. Greene (2002, p.155) suggests to use the non-nested *J*-test of Davidson and Mackinnon (1981) in such cases. Davidson and Mackinnon (1981) formulate the compound model as:

$$r_t = (1-\alpha)(\mu + \beta \mathrm{May}_t + W'_t\delta) + \alpha(\eta + \gamma \mathrm{SAD}_t + W'_t\vartheta) + \varepsilon_t.$$

In this model a test of $\alpha = 0$ would be a test against H_1. However, α cannot be separately estimated in this compound model as it would amount to a redundant scaling of the regression coefficients (Greene, 2002, p. 155). Consequently, Davidson and Mackinnon (1981) developed a two-step methodology which leads to a valid test, at least asymptotically. The first step involves estimating η, γ and ϑ using least squares regression. The second step involves a regression using the estimates obtained in the first step:

$$r_t = (1-\alpha)(\mu + \beta \mathrm{May}_t + W'_t\delta) + \alpha(\hat{\eta} + \hat{\gamma} \mathrm{SAD}_t + W'_t\hat{\vartheta}) + \varepsilon_t.$$

In this equation, testing $\alpha = 0$, is a test against H_1: the specification with the SAD variable, instead of the Halloween dummy. Davidson and Mackinnon (1981) show that the usual t-ratio, $\hat{\alpha}/se(\hat{\alpha})$, is asymptotically distributed as standard normal. Next, we interchange the role of May_t and SAD_t, i.e. H_0 is the model with the SAD variable and H_1

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

Table 2
Orthogonal and non-nested tests for model specification

Explanatory variables	Number of 'correct' signs	Number of 'wrong' signs	Wald test	p-value
Panel A: orthogonal tests				
May_t	33	0	203.7396	*(0.0000)*
$\hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{may}\},t}$	4	0	61.5729	(0.0794)
$\hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{may,temp}\},t}$	6	0	40.7392	(0.7304)
May_t	29	0	206.5373	*(0.0000)*
$\hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{may,SAD}\},t}$	4	1	57.0491	(0.1642)
$\hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{may}\},t}$	4	0	44.8493	(0.5693)
Temp_t	24	3	209.6449	*(0.0000)*
$\hat{\varepsilon}^{may}_{\{temp\},t}$	6	0	51.4491	(0.3228)
$\hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{temp,may}\},t}$	5	0	41.6838	(0.7206)
Temp_t	24	3	216.3244	*(0.0000)*
$\hat{\varepsilon}^{\mathrm{may}}_{\{\mathrm{temp,SAD}\},t}$	4	1	43.4532	(0.6382)
$\hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{temp}\},t}$	7	1	49.1391	(0.4032)
SAD_t	25	2	93.0129	*(0.0000)*
$\hat{\varepsilon}^{\mathrm{may}}_{\{\mathrm{SAD}\},t}$	13	0	67.0372	*(0.0315)*
$\hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{SAD,may}\},t}$	4	2	62.8676	(0.0651)
SAD_t	23	4	93.4593	*(0.0000)*
$\hat{\varepsilon}^{\mathrm{may}}_{\{\mathrm{SAD,may}\},t}$	6	1	57.4722	(0.1511)
$\hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{SAD}\},t}$	8	1	85.4272	*(0.0007)*

H_0	vs.	H_1	Number of cases against H_1
Panel B: non-nested tests			
$r_t = \mu + \beta\mathrm{May}_t + W_t'\delta + \varepsilon_t$	vs.	$r_t = \eta + \gamma\mathrm{SAD}_t + W_t'\vartheta + \varepsilon_t$	13
$r_t = \eta + \gamma\mathrm{SAD}_t + W_t'\vartheta + \varepsilon_t$	vs.	$r_t = \mu + \beta\mathrm{May}_t + W_t'\delta + \varepsilon_t$	1
$r_t = \mu + \beta\mathrm{May}_t + W_t'\delta + \varepsilon_t$	vs.	$r_t = \eta + \gamma\mathrm{Temp}_t + W_t'\vartheta + \varepsilon_t$	7
$r_t = \eta + \gamma\mathrm{Temp}_t + W_t'\vartheta + \varepsilon_t$	vs.	$r_t = \mu + \beta\mathrm{May}_t + W_t'\delta + \varepsilon_t$	2
$r_t = \eta + \gamma\mathrm{Temp}_t + W_t'\vartheta + \varepsilon_t$	vs.	$r_t = \mu + \beta\mathrm{SAD}_t + W_t'\delta + \varepsilon_t$	8
$r_t = \mu + \beta\mathrm{SAD}_t + W_t'\delta + \varepsilon_t$	vs.	$r_t = \eta + \gamma\mathrm{Temp}_t + W_t'\vartheta + \varepsilon_t$	1

Panel A presents the summary of regressions of returns on a seasonal variable and two orthogonal residual variables. The results are obtained from estimating: $r_t = \alpha + \beta_1\mathrm{May}_t + \beta_2\hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{may}\},t} + \beta_3\hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{may,temp}\},t} + W_t'\phi + \varepsilon_t$ where $W_t'\phi = \phi_1 r_t^W + \phi_2\mathrm{JAN}_t + \phi_3\mathrm{NBER}_t$. The unexplained residuals $\hat{\varepsilon}^{\mathrm{temp}}_{\{\mathrm{may}\},t}$ and $\hat{\varepsilon}^{\mathrm{SAD}}_{\{\mathrm{may,temp}\},t}$ are obtained from a temperature and SAD regression: $\mathrm{Temp}_t = \mu + \delta\mathrm{May}_t + \varepsilon^{\mathrm{temp}}_{\{\mathrm{may}\},t}$, and $\mathrm{SAD}_t = \eta + \gamma_1\mathrm{May}_t + \gamma_2\mathrm{Temp}_t + \varepsilon^{\mathrm{SAD}}_{\{\mathrm{may,temp}\},t}$, 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. Panel B presents the non-nested J-test of Davidson and Mackinnon (1981). The J-test is a test of $\alpha = 0$ in $r_t = (1-\alpha)(\mu + \beta\mathrm{May}_t + W_t'\delta) + \alpha(\eta + \gamma\mathrm{SAD}_t + W_t'\vartheta) + \varepsilon_t$. As α cannot be separately estimated in this model, we apply a two-step methodology. Section 2.3 provides more details on both tests.

Notes:

1. The reported p-values in Panel A are based on heteroscedasticity consistent standard errors. Italisized numbers indicate statistical significance at the 5% level (two-sided test).
2. Temp_t denotes the temperature, May_t is the Sell in May dummy, and SAD_t the SAD variable as described in Section 2.2.

the model with the Halloween dummy, such that in the first step the model with Halloween dummy is estimated. This is repeated for all possible combinations of the three seasonal variables. While the J-test is a powerful test, a disadvantage of this approach is that in testing H_0 against H_1 and vice versa, all four possibilities could occur: reject both, neither or either one of the two hypotheses. However, Davidson and Mackinnon (1981) show that this is only a finite sample problem.

The results from the J-tests are presented in Panel B of Table 2, and can be summarized as follows: when testing the model with SAD variable against the May variable, the tests reject thirteen times the model with the SAD variable, in favor of the Sell in May variable. The model with the Sell in May variable is only rejected one time (in favor of the model with the SAD variable). However, the country for which the Sell in May is rejected (Greece) also rejects the other hypothesis (SAD in favor of model with Sell in May). Overall, this suggests strong support for the model with the Sell in May variable. When testing the Sell in May version with the model including the temperature variable, we reject the model with temperature seven times, and the Sell in May model two times. Finally, testing the SAD against the temperature variant, we find that the SAD model is rejected eight times, and the temperature only one time. Overall, the test is very supportive for the

Sell in May variable, and least supportive for a specification with the SAD variable.

An alternative route to follow would be to consider whether we could distinguish between the different explanations using differences between Northern and Southern Hemispheres, the cross-sectional evidence across countries.

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,[23] 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 1 suggests otherwise. Typically, 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 Thailand would react strongly to temperature changes: about seven times as strong as investors from Scandinavian countries. This is surprising, because the standard deviation of monthly temperatures in Thailand is smaller than one degree. One might wonder whether people in Thailand would even be aware of the generally small temperature changes. Similarly, investors in Colombia, Malaysia and Singapore 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 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.

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 opposite to those in the Northern Hemisphere, 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 1 reveals no such evidence. 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 Indonesia, Brazil, South Africa 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 is yet another suggestion that the 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 prevent the results in the Southern hemisphere to be influenced by the Northern Hemisphere results, we run a seemingly unrelated regression (SUR) for all the countries in our sample, as suggested by Cao and Wei (2005). An advantage of the SUR approach to takes the cross-correlation among countries, is that it is not necessary to assume ex-ante a specific return dependency between the countries. The results from estimating the multivariate system are quantitatively similar to ones in Table 1. This indicates that the inter-market correlations cannot explain the negative SAD coefficients for the Southern Hemisphere countries.

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 evidence we report here show that the SAD and temperature arguments are not robust with respect the countries' proximity to the equator, suggesting that it is not likely that the seasonal anomaly in stock returns is caused by mood changes of investors due to lack of daylight and temperature variations.

3. Robustness checks

In this section we perform additional checks to examine the robustness of our results. Our results, and the ones obtained in similar studies, might be prone to various econometric problems, such as model misspecification, measurement errors and inconsistency of parameter estimates. In Section 3.1, we estimate a maximum likelihood model with GARCH effects using (heteroskedasticity and nonnormality) robust standard errors, and we

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

examine the robustness using a general GMM estimation method. Finally, Section 3.2 discusses and tests robustness of our results against the inclusion of several control variables.

3.1. Maximum likelihood estimator with GARCH effects and robust GMM

Using extensive testing, we found evidence of GARCH effects in the data.[24] To account for this we follow the approach suggested by Kamstra et al. (2003a), and estimate all specifications with a maximum likelihood model with GARCH effects and robust *t*-tests. More specifically, we use the sign-GARCH model of Glosten et al. (1993), allowing for asymmetric volatility, and we controlled for heteroskedasticity and produced robust *t*-tests using Bollerslev and Wooldridge (1992) robust (to heteroskedasticity and nonnormality) standard errors. We noted in Section 2.2 that occasionally a temperature observation is missing. As GARCH needs a continuous series to obtain estimates, we replaced the missing observations by the average of the preceding and following observation, and in case of multiple consecutive missing observations, the temperature of the preceding year, resulting in a continuous time series. Table 3 presents the results using maximum likelihood estimator with GARCH effects for the specifications with the temperature, Halloween and SAD variable. Even though we use Bollerslev and Wooldridge (1992) robust standard errors to assess statistical significance which are well known to be conservative, tending to produce insignificant results, the seasonal variables remain significant in most of the countries. Overall, the results do not change qualitatively.

Alternatively, we apply a robust GMM method to estimate the seasonal effect. GMM is a robust estimator in that, unlike the maximum likelihood estimation, it does not require information of the exact distribution of the disturbances. In fact, many common estimators in econometrics can be considered as special cases of GMM. As instruments we include lagged values of the explanatory and explained variable in question. A disadvantage of GMM is that the selection and number of instruments is subjective. It is important to include enough instruments to estimate the models and make sure that there are not too many instruments which would results in a low power, especially if the instruments are irrelevant. The resulting GMM estimates are robust to heteroskedasticity of unknown form. We typically find coefficients on the seasonal variables that are slightly increased in magnitude in absolute terms, and we do still see a strong statistically significant effect of the three seasonal variables. In summary, when considering monthly returns, the use of robust GMM does not make a significant difference in the strength of the explanatory power of the seasonal variables.

3.2. Other robustness checks

The seasonal effects we find for many countries can be caused by seasonality of other variables. However, as has been well documented in the literature, the summer–winter pattern – whatever the cause may be- is remarkably robust. Bouman and Jacobsen (2002) find the effect robust over time and economically significant. They also show that the effect is unrelated to trading volume, interest rate changes and cannot be explained by seasonality in news or risk differences between summer and winter. They control for the January effect and find the effect present in both developed and emerging markets. Kamstra et al. (2003a,b) control for short-term autocorrelation, the Monday effect, tax effects, cloud cover, precipitation and temperature. Cao and Wei (2005) use similar control variables as Kamstra et al. (2003a,b). Additionally, Driesprong et al. (2008) show that the effect is robust with respect to the inclusion of other economic variables that are known to forecast stock returns. They show robustness of the effect against the January effect, dividend yields, inflation, lagged short term interest rates, lagged oil price changes and lagged returns. Jacobsen et al. (2005) find the effect present in the US in all portfolios sorted on size, book to market values, price earnings ratios, dividend yields, cash flow/price ratios and also show that the effects differs from the January effect as contrary to the January effect the summer– winter pattern is a market wide phenomenon. Additionally, they find the effect robust to political cycles and the performance of stock markets during Democratic and Republican presidents, the NBER recession dummy, a momentum effect and a dummy for months with Friday the thirteenth.

Apart from the variables in the previous analysis, we add some other control variables to the list above. Control variables that might make sense and for which one would not expect that they are just white noise with respect to the variables we test, include an October dummy variable, the country-specific P/E ratios and another behavioral variable: the daylight saving time (DST) change dummy for months with a DST switch. We consider whether our findings are robust to the inclusion of these anomalies. From Sections 3.1 and 3.2, we conclude that we can perform the robustness checks using OLS. We first examine the inclusion of a calendar effect: the October effect. Many large historical market crashes occurred during this month. For all countries we test separately the October effect, and we include the corresponding dummies in all the regressions estimated in Section 2.[25] While we find that there is some evidence of the October effect in our dataset, we do not find that these effects affect in any way the significance of the temperature, SAD and Halloween effects. The qualitative nature of the results is very similar to the results reported above in Section 2.

[24] The results of these tests can be obtained from the authors upon request.

[25] All the non-reported results in this section can be obtained from the authors upon request.

Table 3
Maximum likelihood estimates with robust GARCH effects

Country	Latitude	Starting date	Temperature variable		Halloween variable		SAD variable	
			Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Finland	60°31′N	1988:01	−0.06	−0.36	2.37	*1.79*	0.14	0.73
Norway	60°20′N	1970:01	−0.01	−0.41	1.55	*2.31*	0.17	1.20
Sweden	59°65′N	1970:01	−0.08	*−2.35*	1.87	*3.02*	0.33	*2.83*
Russia	55°83′N	1995:01	−0.14	−1.04	3.93	*1.98*	0.78	1.43
Denmark	55°68′N	1970:01	−0.03	−0.80	0.75	*1.83*	0.38	*2.04*
Ireland	53°22′N	1988:01	−0.41	*−2.98*	2.03	*2.54*	0.52	*2.44*
Poland	52°28′N	1993:01	−0.16	−1.34	3.18	*2.58*	1.05	*2.18*
Netherlands	52°10′N	1970:01	−0.10	*−3.18*	1.80	*3.96*	0.27	*2.32*
UK	51°15′N	1970:01	−0.12	*−2.88*	1.26	*2.82*	0.18	1.05
Belgium	50°80′N	1970:01	−0.14	*−3.04*	1.80	*3.89*	0.36	1.49
Germany	50°05′N	1970:01	−0.07	*−1.85*	1.03	*2.15*	0.30	*1.75*
Czech rep.	50°10′N	1995:01	−0.17	−1.23	1.36	1.05	0.43	0.84
France	48°96′N	1970:01	−0.17	*−3.87*	1.64	*2.92*	0.30	*2.04*
Austria	48°25′N	1970:01	−0.06	*−2.65*	0.93	*2.67*	0.23	*2.26*
Hungary	47°51′N	1995:01	−0.20	−1.29	2.83	1.36	1.31	1.42
Switzerland	47°38′N	1970:01	−0.12	*−2.36*	1.31	*2.83*	0.55	*3.21*
Italy	45°27′N	1970:01	−0.22	*−3.05*	2.02	*3.47*	0.53	1.52
Canada	43°41′N	1970:01	−0.03	−1.11	0.81	*1.79*	0.29	*1.67*
Spain	41°28′N	1970:01	−0.11	*−2.18*	1.93	*3.51*	0.58	*1.88*
Turkey	40°96′N	1988:01	−0.38	−1.51	4.64	*3.44*	1.48	1.04
US	40°78′N	1970:01	−0.03	−1.22	0.79	*2.04*	0.19	1.29
Portugal	38°43′N	1988:01	−1.27	*−3.21*	1.72	*2.38*	0.93	*2.59*
Greece	37°96′N	1988:01	−0.13	−1.17	2.12	*1.69*	0.92	1.28
Korea	37°34′N	1988:01	−0.03	−0.85	0.53	0.47	0.39	0.74
Japan	35°41′N	1970:01	−0.18	*−3.83*	1.73	*2.97*	0.48	*1.74*
Morocco	33°35′N	1995:01	−0.25	*−2.22*	1.46	*2.37*	0.69	1.52
Israel	32°60′N	1993:01	−0.09	0.40	0.74	0.69	0.38	0.51
Jordan	31°57′N	1988:01	−0.05	−1.03	1.58	*2.23*	1.62	*2.94*
Pakistan	31°35′N	1993:01	−0.29	*−2.94*	1.02	0.76	2.52	1.61
China	31°16′N	1993:01	0.01	0.26	−0.10	−0.07	0.64	0.51
Egypt	30°13′N	1995:01	−0.48	*−3.38*	4.74	*3.85*	2.70	*1.83*
Hong Kong	22°30′N	1970:01	−0.39	*−1.96*	1.05	1.61	1.94	1.53
Mexico	19°83′N	1988:01	−0.31	−1.08	0.86	0.72	0.84	0.55
India	19°10′N	1993:01	−1.20	*−3.87*	2.85	*2.04*	4.98	1.53
Philippines	14°35′N	1988:01	−0.16	−0.55	1.93	*1.83*	5.73	*2.93*
Thailand	13°73′N	1988:01	−0.40	−0.76	2.69	*2.05*	6.83	*2.79*
Venezuela	10°50′N	1993:01	−0.15	−0.29	0.54	0.31	2.89	0.56
Sri Lanka	6°90′N	1993:01	1.63	0.84	−1.05	−0.70	−0.83	−0.41
Colombia	4°36′N	1993:01	−0.95	−0.77	3.06	*2.89*	21.81	*1.93*
Malaysia	3°70′N	1988:01	−0.89	−1.05	2.29	*2.57*	13.87	1.18
Singapore	1°18′N	1970:01	−1.10	*−2.85*	1.29	*2.37*	29.58	*3.65*
Indonesia	6°11′S	1988:01	−2.65	*−2.05*	2.88	*1.79*	−5.39	*−3.05*
Brazil	23°50′S	1988:01	0.38	1.22	3.48	*2.43*	−2.59	*−1.84*
South Africa	26°13′S	1993:01	0.28	*2.36*	1.69	*2.38*	−1.02	−1.23
Australia	33°85′S	1970:01	0.14	1.53	1.55	*2.19*	−0.68	*−2.26*
Chile	34°10′S	1988:01	0.27	*2.03*	1.72	*1.88*	−7.48	*−1.90*
Argentina	34°58′S	1988:01	0.02	1.34	3.49	1.44	−2.42	*−2.03*
New Zealand	41°17′S	1988:01	0.17	1.39	1.85	*2.49*	−0.21	−0.60

This table presents the results of regressions using temperature, Halloween and SAD variable; ordered on latitude.
Notes:
1. Ending date for all series is 2004:05. Coeff. denotes estimated coefficient; *t*-stat. denotes the corresponding *t*-statistic.
2. The reported *t*-statistics are based on the Bollerslev and Wooldridge (1992) robust standard errors. Italisized numbers indicate statistical significance at the 5% level (one-sided test).
3. The coefficients are scaled by a factor 100.

We find similar results if we control for the country-specific earnings–price ratios. The earnings–price ratio is an interesting control variable to consider as earnings typically depend on the season. We find that only for France, Singapore and Switzerland the coefficient of the P/E ratio is statistically significant. For the other countries there is no clear evidence of any relation with the monthly P/E ratio and the stock market returns. After including the

P/E ratio's, especially the SAD effects becomes typically less strong. However, all three seasonal effects remain significantly present in the data.

Another behavioral factor which has been suggested in the literature to cause mood changes in investors' behavior is the daylight saving time change. According to a study by Kamstra et al. (2000), investors might alter their trading behavior around daylight saving time (DST) weekends, due to changes in their sleep patterns. Their evidence suggests that daylight saving weekends are typically followed by large negative returns in market indices.[26] We include two DST dummies in the regression equations, where one dummy takes the value one in the months in which there has been a switch to DST, and the other take the value one in the months in which there has been a switch from DST (the dummies take the value zero in all other cases). While we find that for some countries there is a significant DST effect, this finding is quite weak. The evidence of the DST effect becomes even weaker after one of the weather-related variables has been included. On the other hand, there is no change in the temperature, SAD and Halloween effect. Thus, DST does not explain the seasonal pattern in international stock returns. The seasonal effect is robust and the only variables that seem to 'explain' the seasonal effect are any variables with a strong summer–winter seasonal. Note that the results seem very robust. Changing the specification of the basic model, by leaving out control variables or including new control variables results in a situation in which the seasonal effect of the weather-related variables remain robust.

4. Conclusion

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. Our analysis shows that it is simply not enough to link temperature and SAD directly to stock returns on the assumption that these variables affect mood and therefore affect stock returns. We show that other variables with a strong seasonal pattern do at least as well; the Sell in May/Halloween variable, for example, seems to explain the stock market seasonality very well. As in many other cases the 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 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 an old market wisdom. The problem is that many variables are correlated with the seasons and it is hard to distinguish among them when trying to 'explain' seasonal patterns in stock returns.[27] Depending on one's believes one might favor one explanation over the other. However, we report some evidence that modeling the seasonality as a SAD effect leaves some unexplained seasonality. Moreover, non-nested tests show that a model specification with the Halloween dummy is superior to specifications with temperature or SAD as explanatory variable. Furthermore, our cross-sectional analysis suggests that the SAD and temperature arguments are not robust with respect the countries' proximity to the equator.

The important question remains what causes this effect. Interesting in this respect is the recent evidence in Kamstra et al. (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 et al. (2003b) choose to attribute this change to SAD. In this respect, their study suffers from the same problem as Kamstra et al. (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 Tavassoli (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. Finally, the seasonal effect is robust to different specifications, estimation techniques and addition of control variables. The only variables that seem to 'explain' the seasonal effect are any variables with a strong summer–winter seasonal.

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. Not only does this seem the best choice based on our analysis above, but this has the advantage that one does not need temperature data or complicated trigonometric formulas. Moreover, 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

[26] Although one may argue whether a DST effect in stock return exists. Gregory-Allen et al. (2006), for instance, find no evidence of a DST effect in 20 stock markets around the world.

[27] In fact, in an earlier version of the paper, we found that two other variables with a similar seasonal pattern (US ice consumption and UK air line travel) also 'explained' stock returns extremely well.

Goetzmann and Zhu (2005) and Theissen (2007). 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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