Winter Blues: A SAD Stock Market Cycle

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> And God said, Let there be light; and there was light. And God saw that the light was good.
>
> Genesis 1:3

Depression has been linked with seasonal affective disorder (SAD), a condition that affects many people during the seasons of relatively fewer hours of daylight. Experimental research in psychology has documented a clear link between depression and lowered risk-taking behavior in a wide range of settings, including those of a financial nature. Through the links between SAD and depression and between depression and risk aversion, seasonal variation in length of day can translate into seasonal variation in equity returns. Based on supportive evidence from psychology which suggests SAD is linked closely with hours of daylight, we consider stock market index data from countries at various latitudes and on both sides of the equator. We model differences in the seasonal variation of daylight across countries to capture the influence of daylight on human sentiment, risk tolerance, and hence stock returns. Our results strongly support a SAD effect in the seasonal cycle of stock returns that is both significant and substantial, even after controlling for well-known market seasonals and other environmental factors. Patterns at different latitudes and in both hemispheres provide compelling evidence of a link between seasonal depression and seasonal variation in stock returns: higher-latitude markets show more pronounced SAD effects and results in the Southern Hemisphere are six months out of phase, as are the seasons.

The remainder of the paper is organized as follows. In Section I, we discuss SAD, depression, and equilibrium market returns. In Section II, we introduce the international data sets. In Section III, we explain the construction of the variables intended to capture the influence of SAD on the stock market. We document in Section IV the significance of the SAD effect, both statistical and economic, and provide an example of the excess returns that arise from trading strategies based on the SAD effect. In Section V, we explore the robustness of the SAD effect to changes in variable definitions and estimation methods. Section VI considers SAD in the context of segmented versus integrated capital markets. Section VII concludes.[1]

I. SAD and the Stock Market

As John Keats has written, "Four seasons fill the measure of the year. There are four seasons in the mind of man." One important aspect of the seasons as they affect the mind is the reduced daylight hours during the fall and winter months. According to Norman E. Rosenthal (1998), the recurrent problems associated with

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[1] An Appendix to this paper is available at www.markkamstra.com or from the authors on request. The Appendix provides detailed estimation results from Kamstra et al. (2000) as well as further robustness and sensitivity checks described but not provided below.

diminished daylight take on a particularly severe form among the approximately 10 million Americans who are afflicted with seasonal affective disorder, where "affective" means emotional. A further 15 million suffer a milder form, "winter blues." The problem is also extensively documented outside the United States, with similar proportions of sufferers in countries around the world.[2] Jeanne Molin et al. (1996) and Michael A. Young et al. (1997) provide evidence that seasonal depression is related to hours of daylight, and hence the effects of SAD may be more pronounced in countries at more extreme latitudes where winter and fall days are relatively shorter.

SAD is clinically defined as a form of major depressive disorder.[3] While usually described in terms of prolonged periods of sadness and profound, chronic fatigue, evidence suggests that SAD is connected to serotonin dysregulation in the brain. Furthermore, positron emission tomography (PET) scans reveal abnormalities in the prefrontal and parietal cortex areas due to diminished daylight, as described in the National Institute of Mental Health study by Robert M. Cohen et al. (1992). That is, there appears to be a physiological source to the depression related to shorter days. SAD symptoms include difficulty concentrating, loss of interest in sex, social withdrawal, loss of energy, lethargy, sleep disturbance, and carbohydrate or sugar craving often accompanied by weight gain.[4] For those affected, the annual onset of SAD symptoms can occur as early as September, around the time of autumn equinox. See Steven C. Dilsaver (1990), for example.

Experimental research in psychology has documented a direct link between depression and heightened risk aversion. This link is established by first providing a measure of risk-taking tendency in the form of a scale of "sensation-seeking" propensity, the most widely used of which was developed by Marvin Zuckerman (1984). The scale is then correlated with various biological and psychological phenomena, as shown, for example, by Zuckerman et al. (1980). Sensation-seeking measures used to judge the propensity to take risk have been extensively documented as reliable measures of risk-taking tendency in financial decision-making settings by Alan Wong and Bernardo Carducci (1991), Paula Horvath and Zuckerman (1993), and Howard Tokunaga (1993), among others. When the willingness to take risk is related to measured levels of anxiety and depression, there is a distinct tendency for greater anxiety or depression to be associated with reduced sensation seeking and reduced general willingness to take risk, as shown by Zuckerman (1984, 1994), Gregory A. Marvel and Barbara R. Hartman (1986), Solange Carton et al. (1992), and Carton et al. (1995). In a further study of depression and risk aversion, Amy E. Eisenberg et al. (1998) conducted experiments in which subjects differing in degree of depression were faced with a series of choices between pairs of risky and safe options, including some of a financial nature. By setting the choices such that in some cases the risky option was the default (not requiring action) and in other cases the safe option was the default, the researchers were able to distinguish risk aversion from passivity: depressive symptoms correlated with risk aversion.

The psychological studies cited above strongly support the view that the depression associated with shorter days translates into a greater degree of risk aversion, leading to testable hypotheses in the context of stock market returns. Those market participants directly affected by SAD can influence overall market returns according to the well-established principle that market equilibrium occurs at prices where marginal buyers are willing to exchange with marginal sellers: aggregate demands and supplies for risky versus riskless assets can thereby affect equilibrium risk premia.[5] The

[2] For example, the frequency of SAD in northern Canada is documented by Robert J. Williams and G. G. Schmidt (1993). The incidence of SAD in Italy is discussed by Gianni L. Faedda et al. (1993). There is even evidence, from the Mayo Clinic (2002), that SAD occurs in countries as close to the equator as India. These and others studies suggest approximately 10 percent of people suffer from SAD.

[3] See, for example, David H. Avery et al. (1993), Ybe Meesters et al. (1993), Georg Leonhardt et al. (1994), and R. Michael Bagby et al. (1996).

[4] Mayo Clinic (2002).

[5] For further details on the impact of the marginal trader on market equilibria, see the classic papers by John R. Hicks (1963) and Gerald O. Bierwag and M. A. Grove (1965), as

implication is a causal relationship between seasonal patterns in length of day and market returns.

Studies on individuals at extreme latitudes, including work by Lawrence A. Palinkas et al. (1996) and Palinkas and Matt Houseal (2000), suggest the depressive effects of SAD and hence risk aversion may be asymmetric about winter solstice. Thus two dates symmetric about winter solstice have the same length of night but possibly different expected returns. We anticipate seeing unusually low returns before winter solstice and abnormally high returns following winter solstice. Lower returns should commence with autumn, as SAD-influenced individuals begin shunning risk and rebalancing their portfolios in favor of relatively safe assets. We expect this to be followed by abnormally high returns when days begin to lengthen and SAD-affected individuals begin resuming their risky holdings. As long as there are SAD sufferers shunning risk at some times of the year relative to other times, market returns will contain a seasonal. According to the medical evidence on the incidence of SAD, this seasonal relates to the length of the day, not to changes in the length of the day. Therefore, against the null hypothesis that there is no effect of the seasons related to SAD and the winter blues, our alternative hypothesis is that seasonal depression brought on by short days lead to relatively lower returns in the fall and relatively higher returns in the winter.

A. *Length of Night and Other Environmental Factors*

A related literature in economics investigates the influence of weather on market returns. As argued by Edward M. Saunders (1993) and David Hirshleifer and Tyler Shumway (2003), the number of hours of sunshine affects peoples' moods and hence also possibly market returns. The amount of sunshine is affected by cloud cover as well as the number of hours of daylight, and indeed, Saunders (1993) uses a measure of cloudiness by classifying the degree of cloudiness in New York City into three categories: 0–30 percent; 40–70 percent; 80–100 percent, and finds support for a relation between sunshine and market returns. Hirshleifer and Shumway (2003) present further evidence for a sunshine effect in a study of 26 international stock markets. Instead of studying sun or cloud, Melanie Cao and Jason Wei (2001) investigate the influence of temperature on stock market returns and find evidence of a link in eight international markets. All of these studies consider weather at the level of cities in which the markets are located.

Molin et al. (1996) show that among several environmental factors (minutes of sunshine, length of day, temperature, cloud cover, precipitation, global radiation, and barometric pressure), length of day has the strongest correlation with seasonal depression. They employ stepwise regression to reduce their multiple regression model to include only length of day and temperature from the set of all the environmental variables considered. Young et al. (1997) provide further evidence that SAD is related to the length of day by studying latitude. Our study builds on the psychology literature linking seasonal affective disorder to length of day as well as the economics literature linking environmental factors to stock market returns. Thus we test for a relationship between length of night and stock returns, controlling for other environmental factors which may influence returns, including cloud cover, precipitation, and temperature.

II. Market Returns Data

The daily stock index return data used in this study are outlined in Table 1: four indices from the United States as well as indices from eight other countries, chosen to represent large-capitalization, broad-based economies at different latitudes in both hemispheres.[6,7] We include

well as the Appendix, "The Equilibrium Prices of Financial Assets," by James C. Van Horne (1984, pp. 70–78).

[6] Our selection of indices was dictated by several criteria, including the availability of a sufficiently long time series, the absence of hyperinflation, large capitalization, and representation of a broad range of sectors.

[7] All of our foreign stock market returns were obtained from Datastream. A feature of the Datastream time series is that they often include nontrading days such as holidays. Datastream typically assigns a value on a nontrading day equal to the previous day's price or equivalently a zero return. To remove holidays, we made use of Datastream's vacation files (when available), which track various countries' holidays (starting no earlier than 1985), augmented by

TABLE 1—DAILY STOCK INDEX RETURN DATA WITH CORRESPONDING CITIES AND LATITUDES

Country	Index	City	Latitude
United States	S&P 500	New York	41°N
United States	NYSE	New York	41°N
United States	NASDAQ	New York	41°N
United States	AMEX	New York	41°N
Sweden	Veckans Affärer	Stockholm	59°N
Britain	FTSE 100	London	51°N
Germany	DAX 30	Frankfurt	50°N
Canada	TSE 300	Toronto	43°N
New Zealand	Capital 40	Auckland	37°S
Japan	NIKKEI 225	Tokyo	36°N
Australia	All Ordinaries	Sydney	34°S
South Africa	Datastream Global Index	Johannesburg	26°S

Note: Latitudes are rounded to the nearest degree and reflect the location of the city corresponding to each index's stock exchange.

the largest exchange among the far northerly markets (Stockholm, Sweden) and the largest exchange in the Southern Hemisphere (Sydney, Australia). Our longest time series is the U.S. S&P 500, which spans over 70 years. The longest spanning index we could obtain for South Africa is the Datastream Global Index of 70 large-cap stocks in that country. All of the indices we consider are value-weighted returns excluding dividend payments. For the United States we also investigated CRSP equal-weighted indices and CRSP indices of returns including dividends, and as shown in the Appendix (available from the authors), we found qualitatively identical results in all cases. The relevance of market segmentation/integration across markets at different latitudes is addressed in Section VI.

Table 2 displays simple summary statistics for the raw data used in this study, the daily percentage returns for the four indices in the United States, and an index for each of Sweden, Britain, Germany, Canada, New Zealand, Japan, Australia, and South Africa. Directly below the name of each country is the period over which the returns were collected. The sample sizes range from under 3,000 daily observations for New Zealand to over 19,000 for the U.S. S&P 500 index. The first column of statistics is the daily percentage mean return. The mean daily return is of the same order of magnitude for all of the indices, ranging from about 0.01 percent to 0.06 percent. Standard deviation of the daily returns varies across countries, with South Africa being the most volatile (unconditionally) at 1.34 percent and the U.S. NYSE and AMEX the least volatile, at 0.84 percent. The largest single-day drop, a decline exceeding 28 percent, was experienced in Australia during the October 1987 crash. The largest single day gains ranged from 7.60 percent to 15.37 percent. All of the return series are strongly skewed to negative returns, as is typical with stock market returns. All the return series are strongly kurtotic as well. Conventional tests of normality (not reported) strongly reject the hypothesis that any of these return series are normally distributed, as is also typical with stock market returns.

The returns data are summarized in an aggregate form in Figures 1 and 2. Figure 1 plots the monthly means of the daily percentage returns averaged across all four of the United States indices. The graph shows that in September, the month in which the onset of autumn occurs, returns are on average at their lowest point of the year. They gradually recover through the fall, and then in winter they become positive and peak in January, the first month following winter solstice. Speaking very roughly there is an indication in the data of some sort of cycle through fall and winter. The raw data suggest that September and January may be extreme points on a seasonal cycle.

information on foreign holidays gleaned from various sources including the Worldwide Holiday & Festival Site (www.holidayfestival.com). As shown in the Appendix (available from the authors), we find qualitatively identical results whether controlling for holidays as described above or omitting all zero return days.

TABLE 2—DAILY PERCENTAGE RETURN SUMMARY STATISTICS FOR EACH INDEX

Country and period	Mean	Standard deviation	Minimum	Maximum	Skew	Kurtosis
United States: S&P 500 1928/01/04–2000/12/29	0.024	1.12	−20.47	15.37	−0.35	18.90
United States: NYSE 1962/07/05–2000/12/29	0.035	0.84	−18.36	8.79	−1.16	28.76
United States: NASDAQ 1972/12/18–2000/12/29	0.047	1.10	−11.35	10.57	−0.48	12.08
United States: AMEX 1962/07/05–2000/12/29	0.032	0.84	−12.75	10.56	−0.86	16.41
Sweden 1982/09/15–2001/12/18	0.063	1.25	−8.986	9.78	−0.25	6.02
Britain 1984/01/04–2001/12/06	0.037	1.01	−13.03	7.60	−0.93	12.29
Germany 1965/01/05–2001/12/12	0.025	1.10	−13.71	8.87	−0.50	8.62
Canada 1969/01/03–2001/12/18	0.023	0.85	−10.29	9.88	−0.75	13.97
New Zealand 1991/07/02–2001/12/18	0.013	0.97	−13.31	9.48	−0.86	18.78
Japan 1950/04/05–2001/12/06	0.037	1.12	−16.14	12.43	−0.34	10.82
Australia 1980/01/03–2001/12/18	0.033	1.00	−28.76	9.79	−4.89	131.49
South Africa 1973/01/03–2001/12/06	0.054	1.34	−14.53	13.57	−0.72	9.69

Note: All indices are value-weighted and do not include dividend distributions.

Figure 2 plots the monthly means of the daily percentage returns averaged across the eight foreign indices. Prior to averaging the returns, the data for Australia, New Zealand, and South Africa were shifted six months to adjust for the difference in seasons across the hemispheres. Note that returns are not shifted in this manner for any other figure or table in the paper. The horizontal axis (in Figure 2 only) is labeled with reference to timing in the Northern Hemisphere. That is, the first observation is an average of returns over the month in which autumn begins in each country, September for the Northern Hemisphere countries and March for the Southern Hemisphere countries. In Figure 2, we observe the lowest average return in the month in which the onset of autumn occurs for all countries, marked September, and the highest average return occurs in the month following winter solstice, marked January. Overall the graph exhibits what may be interpreted as a seasonal pattern similar to that shown in Figure 1.

Figures 3, 4, and 5 plot monthly means of daily percentage returns for each of the individual indices considered in this paper. Panels A through D of Figure 3 plot monthly mean returns for the United States indices. Panels A through D of Figure 4 plot the monthly means for Sweden, Britain, Germany, and Canada, and Panels A through D of Figure 5 plot monthly mean returns for New Zealand, Japan, Australia, and South Africa. (The horizontal axis of the plot for each country starts with the month in which autumn equinox actually takes place in that country, March in the Southern Hemisphere and September in the Northern Hemisphere.) Each of the U.S. indices shown in Figure 3 demonstrate the same approximate pattern: lowest annual returns in the early fall months followed by increasing returns peaking in the first month of the year. Similarly, for each of the countries shown in Figure 4, returns are at their lowest in September and then they peak shortly after winter solstice. The countries in Figure 5 are the four closest to the equator among those we consider, and thus we would expect to see less of a seasonal in these countries' returns. While the pattern for Japan's returns is similar to those we have observed for other countries, the patterns for South Africa, Australia, and New Zealand seem more random in nature. Regarding all the individual plots shown in Figures 3, 4, and

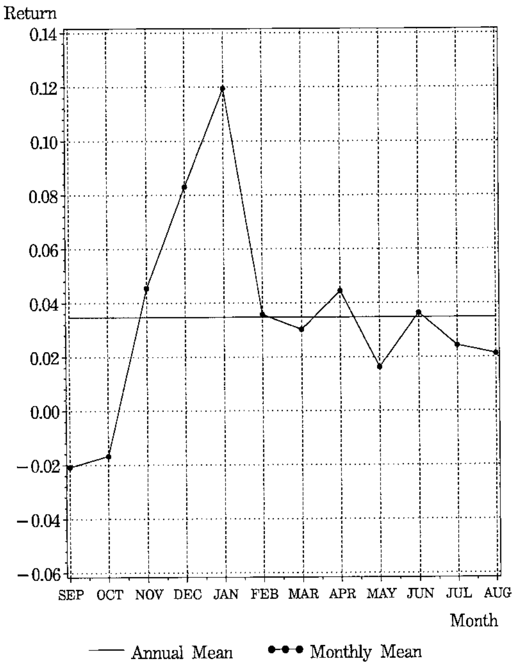

FIGURE 1. COMPOSITE PLOT FOR THE UNITED STATES INDICES

Notes: The Annual Mean represents the daily percentage returns averaged over the year across all four U.S. indices. The Monthly Mean represents the daily percentage returns averaged over each month across all seven value-weighted indices.

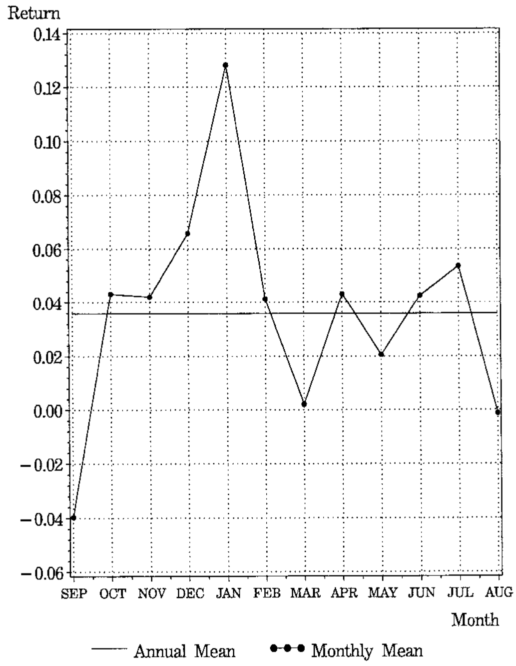

FIGURE 2. COMPOSITE PLOT FOR FOREIGN INDICES

Notes: The Annual Mean represents the daily percentage returns averaged over the year across all eight foreign indices. The Monthly Mean represents the daily percentage returns averaged over each month across all eight foreign indices. In producing this figure only, returns from indices in the Southern Hemisphere are shifted by six months to align the seasons, and then the horizontal axis is marked with reference to the timing in the Northern Hemisphere.

5, although the average annual patterns vary somewhat, they typically show weak mean returns in early autumn followed by strong returns shortly after the longest night of the year. Broadly speaking, the returns drop thereafter and flatten out through the spring and summer. The Southern Hemisphere exchanges, unconditionally at least, do not follow the same pattern in the fall, though perhaps it is not a surprise to find a lack of seasonal patterns in the exchanges located closest to the equator where seasonal fluctuations in daylight are small.

III. Measuring the Effect of SAD

In describing the seasonal pattern of light through the course of the year, one could equivalently consider the number of hours of day, from sunrise to sunset, or the number of hours of night, which simply equals 24 minus the number of hours of day. We choose the latter. Figure 6 shows the cycles for the length of the night for several of the countries included in this study. For simplicity, the cycles shown in Figure 6 reflect the length of night for the latitude at which a country's stock exchange is located, rounded to the nearest degree. The length of the night during the course of the year peaks in the Northern Hemisphere on the winter solstice, December 21st, and reaches a trough on the summer solstice, June 21st.[8] In the Southern Hemisphere, the function is six months out of phase, with its peak on June 21st and trough on December 21st. The variations in the length of night are larger the further away one travels

[8] For convenience we assume winter solstice takes place on December 21 and summer solstice on June 21. In practice the timing can vary by a couple of days.

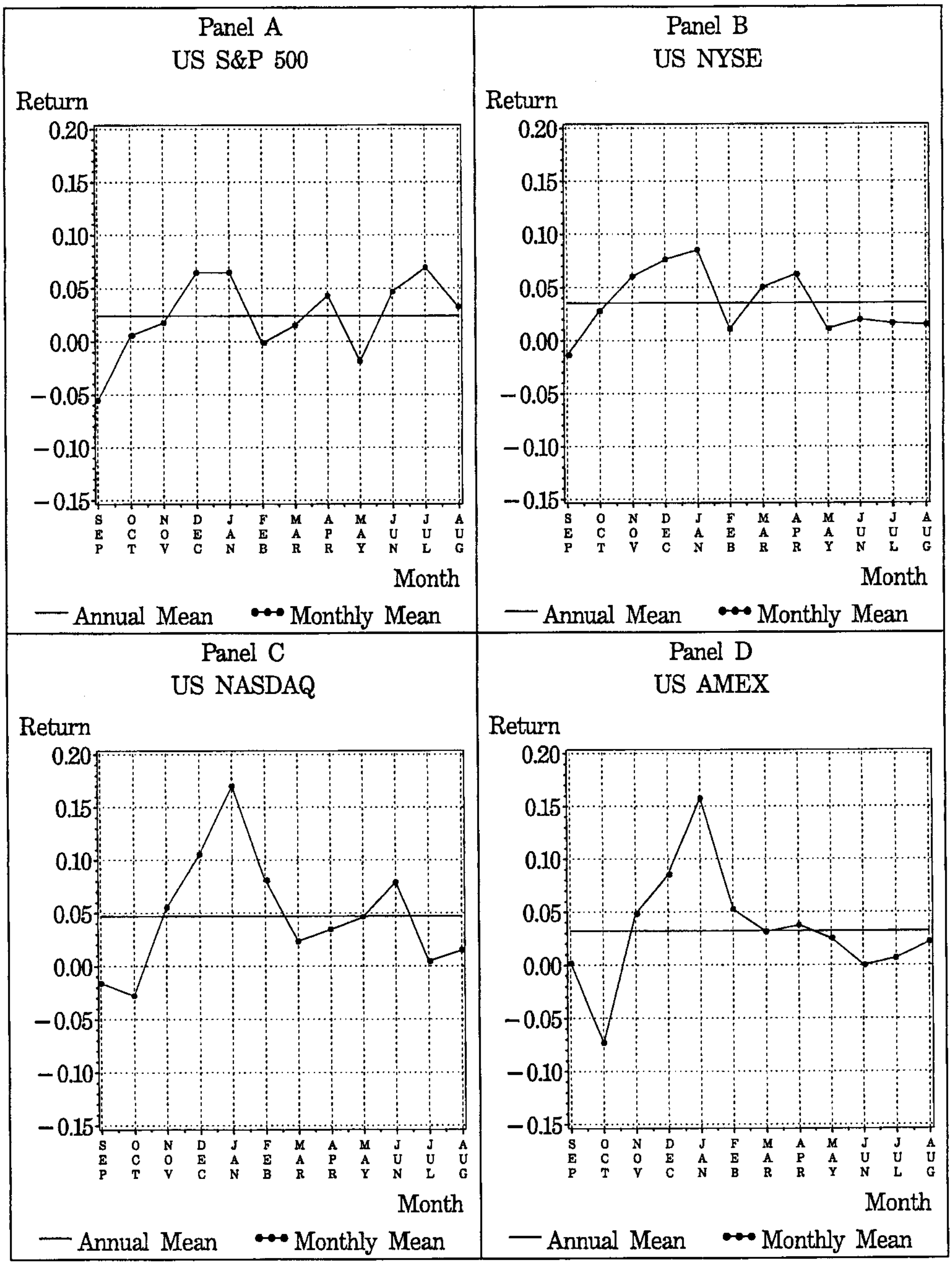

FIGURE 3. INDIVIDUAL PLOTS OF DATA FOR EACH OF THE UNITED STATES INDICES

Notes: The Annual Mean for each index represents the daily percentage returns averaged over the year for that index. The Monthly Mean for each index represents the daily percentage returns averaged over each month for that index.

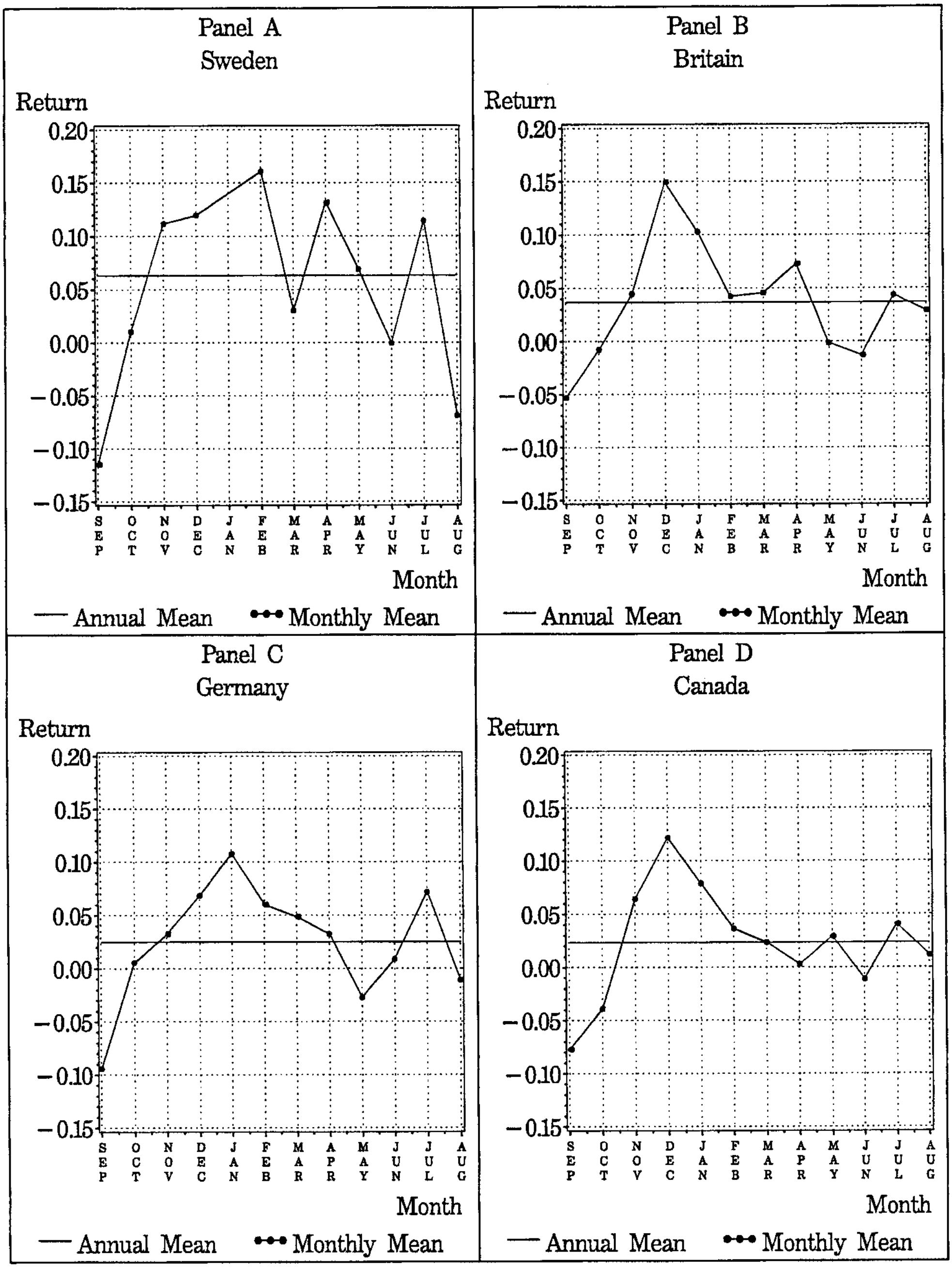

FIGURE 4. INDIVIDUAL PLOTS OF DATA FOR SWEDEN, BRITAIN, GERMANY, AND CANADA

Notes: The Annual Mean for each index represents the daily percentage returns averaged over the year for that index. The Monthly Mean for each index represents the daily percentage returns averaged over each month for that index.

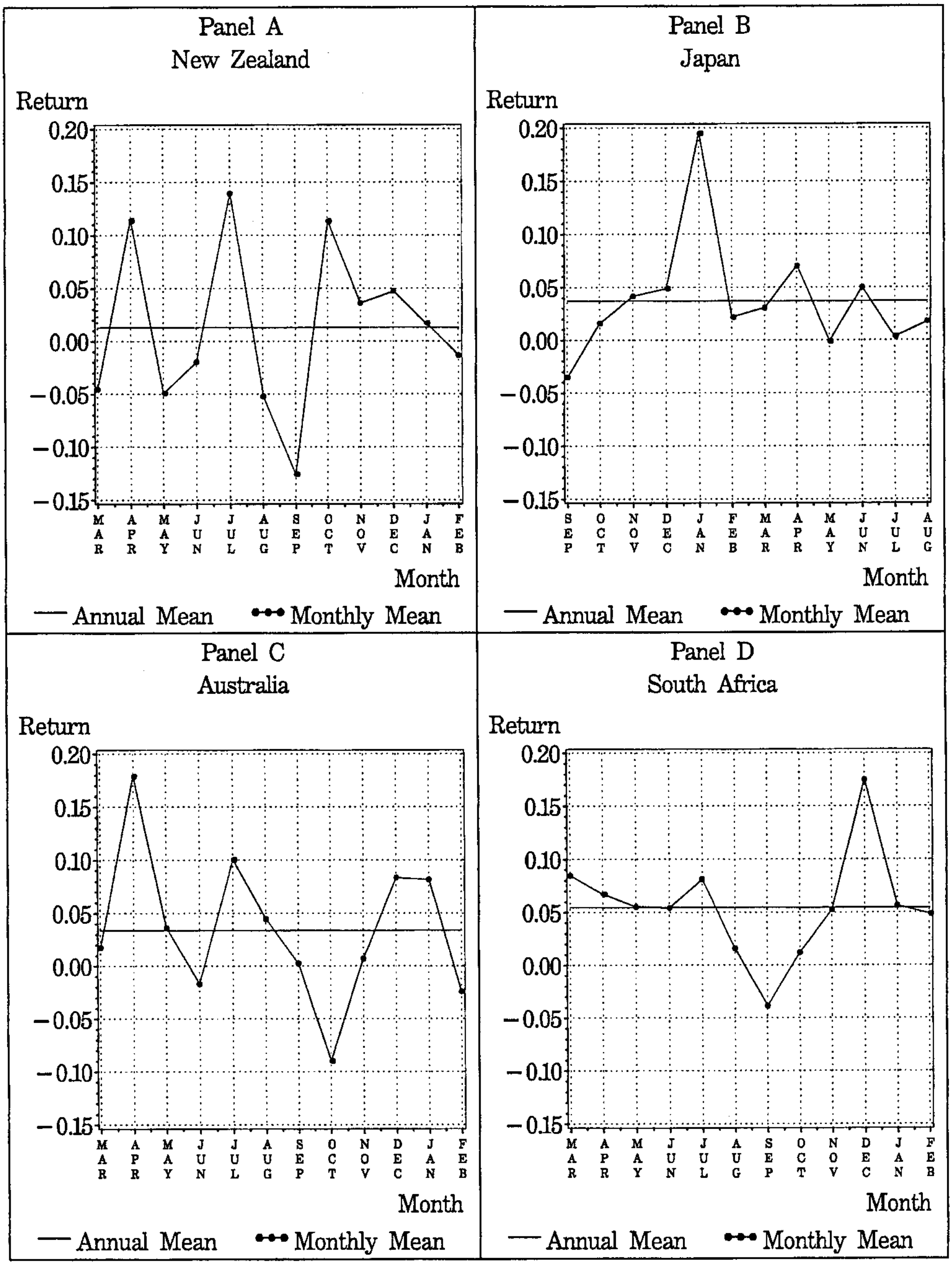

FIGURE 5. INDIVIDUAL PLOTS OF DATA FOR NEW ZEALAND, JAPAN, AUSTRALIA, AND SOUTH AFRICA

Notes: The Annual Mean for each index represents the daily percentage returns averaged over the year for that index. The Monthly Mean for each index represents the daily percentage returns averaged over each month for that index.

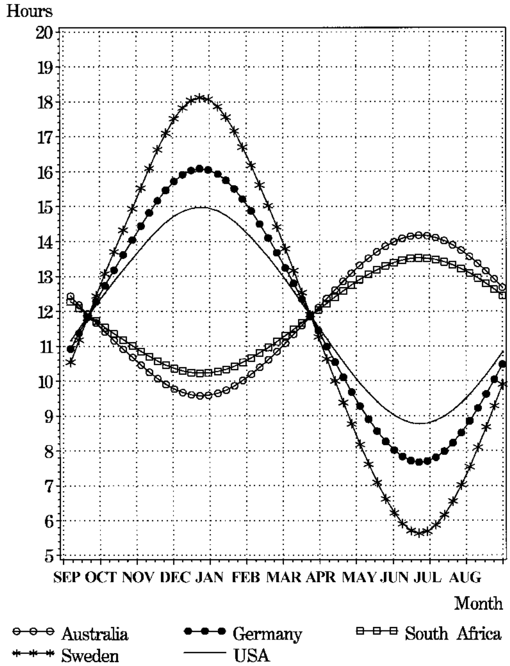

FIGURE 6. HOURS OF NIGHT FOR SEVERAL MARKETS

Notes: Actual hours of night are shown for the latitudes at which various countries' stock exchanges are located (rounded to the nearest degree). The latitudes, in degrees, are as follows: 26 South for South Africa, 34 South for Australia, 41 North for the United States, 50 North for Germany, and 59 North for Sweden.

from the equator, i.e., the larger is the latitude north or south. Thus, among the countries we consider, Sweden experiences much greater variability relative to countries closer to the equator, like South Africa and Australia.

As described above, medical evidence indicates that variation in the amount of daylight during the fall and winter has a systematic effect on individuals' moods. Thus we use the number of hours of night during only the fall and winter to capture the effects of SAD on markets. In Section V, we discuss the similarity of results that arise using alternate specifications that allow for SAD-related effects through all four seasons.

The length-of-night measure we use to capture the effects of SAD on the stock market has some desirable features. First, it allows us to see whether there are more pronounced stock market effects due to SAD in countries at more extreme latitudes where the fall and winter months have relatively shorter days. Second, the measure varies similarly across entire countries and even hemispheres; thus wherever a marginal trader happens to be located within a country, her degree of seasonal depression and hence her influence on markets would be expected to manifest similarly.

A. *SAD Measure Based on Normalized Hours of Night*

Define H_t as the time from sunset to sunrise at a particular location. Then we can define our SAD measure, SAD_t, at that location as follows[9]:

$$(1)\quad SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise.} \end{cases}$$

Note that SAD_t varies only over the fall and winter, the seasons when according to medical evidence SAD affects individuals. By deducting 12 (roughly the average number of hours of night over the entire year at any location), SAD_t reflects the length of the night in the fall and winter relative to the mean annual length of 12 hours. In Sweden, for example, the SAD_t variable equals 0 at the autumn equinox (September 21), takes on higher values until it peaks at +6 on winter solstice, then takes on lower values until it equals 0 at the spring equinox (March 20), and remains at 0 through the spring and summer. For countries closer to the equator, the value varies relatively closer to 0 during the fall and winter.

The number of hours of night, H_t, can be determined using standard approximations from spherical trigonometry as follows. To calculate the number of hours of night at latitude δ we first need the sun's declination angle, λ_t:

(2)

$$\lambda_t = 0.4102 \cdot \sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80.25)\right]$$

[9] The fall and winter period is defined as September 21 to March 20 for the Northern Hemisphere and March 21 to September 20 for the Southern Hemisphere. We assume the fall and spring equinoxes take place on September 21 and March 21, though the actual timing can vary by a couple of days.

where $julian_t$ is a variable that ranges from 1 to 365 (366 in a leap year), representing the number of the day in the year. $Julian_t$ equals 1 for January 1, 2 for January 2, and so on. We can then calculate the number of hours of night as:

(3)

$$H_t = \begin{cases} 24 - 7.72 \cdot \arccos\left[-\tan\left(\dfrac{2\pi\delta}{360}\right)\tan(\lambda_t)\right] \\ \quad \text{in the Northern Hemisphere} \\ 7.72 \cdot \arccos\left[-\tan\left(\dfrac{2\pi\delta}{360}\right)\tan(\lambda_t)\right] \\ \quad \text{in the Southern Hemisphere} \end{cases}$$

where arccos is the arc cosine.

B. *Asymmetry Around Winter Solstice*

There are at least two reasons to expect the length of night to lead to an asymmetric response in market returns before winter solstice relative to after. First, as mentioned in Section I, results from Palinkas et al. (1996) and Palinkas and Houseal (2000) indicate the depressive effect of SAD may be asymmetric around winter solstice. Second, the trading activity of SAD-affected investors may itself cause asymmetric patterns in equity returns. Specifically, if investors become more risk averse at the onset of fall and then return to "normal" at the end of winter, higher compensating returns for holding risky assets between those points in time are generated by an initial price which is lower than would otherwise have been observed. That is, with the onset of heightened risk aversion associated with SAD, prices rise less quickly than they would otherwise. After levels of risk aversion return to their previous, non-SAD influenced levels at the end of winter, the recovery of prices from their initial (lower) levels increases returns. The implication is that returns are lower in the fall and higher in the winter.

In order to allow for an asymmetric effect in the fall relative to the winter, we introduce a dummy variable for days of the year which are in the fall season[10]:

$$(4) \quad D_t^{Fall} = \begin{cases} 1 & \text{for trading days in the fall} \\ 0 & \text{otherwise.} \end{cases}$$

Including this dummy variable allows (but does not require) the impact of SAD in the fall to differ from that in the winter. If, contrary to our expectations, the effects are symmetric across the two periods, this will simply be reflected by a coefficient on D_t^{Fall} which is insignificantly different from zero.

IV. Influence of the SAD Effect

A. *Estimation*

We run a single regression for each country, allowing the impact of SAD to vary freely from country to country. Returns are regressed on up to two lagged returns (where necessary to control for residual autocorrelation), a Monday dummy, a dummy variable for a tax-loss selling effect, the SAD measure, a fall dummy, cloud cover, precipitation, and temperature.[11]

(5)

$$\begin{aligned} r_t = {} & \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \mu_{Monday} D_t^{Monday} \\ & + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} \\ & + \mu_{Cloud} Cloud_t \\ & + \mu_{Precipitation} Precipitation_t \\ & + \mu_{Temperature} Temperature_t + \varepsilon_t. \end{aligned}$$

[10] Fall is defined as September 21 to December 20 in the Northern Hemisphere and March 21 to June 20 in the Southern Hemisphere.

[11] The use of the AR(1) specification for stock returns is common, as is the use of Monday and tax-loss dummy variables. See, for instance, Vedat Akgiray (1989), Adrian Pagan and William Schwert (1990), Raul Susmel and Robert F. Engle (1994), and R. Glen Donaldson and Kamstra (1997). Seasonality in stock returns is explored in a wide range of papers including Nai-Fu Chen et al. (1986), Eric C. Chang and J. Michael Pinegar (1989, 1990), and Sven Bouman and Ben Jacobsen (2002). There are numerous papers that study seasonal stock market effects as related to tax-loss selling, including Philip Brown et al. (1983), Seha M. Tinic and Richard R. West (1984), Kiyoshi Kato and James S. Schallheim (1985), Richard H. Thaler (1987), Jay R. Ritter (1988), Steven L. Jones et al. (1991), Ravinder K. Bhardwaj and LeRoy D. Brooks (1992), George Athanassakos and Jacques A. Schnabel (1994), Charles Kramer (1994), and James A. Ligon (1997).

Variables are defined as follows: r_t is the period t return for a given country's index, r_{t-1} and r_{t-2} are lagged dependent variables, D_t^{Monday} is a dummy variable which equals one when period t is the trading day following a weekend (usually a Monday) and equals zero otherwise, D_t^{Tax} is a dummy variable which equals one for a given country when period t is in the last trading day or first five trading days of the tax year[12] and equals zero otherwise, and D^{Fall} is a dummy variable which equals one for a given country when period t is in the fall and equals zero otherwise. The environmental factors, each measured in the city of the exchange, are percentage cloud cover ($Cloud_t$), millimeters of precipitation ($Precipitation_t$), and temperature in degrees Celsius ($Temperature_t$).[13]

At the end of this subsection we discuss the results from estimating equation (5). (Most importantly, the parameter estimates on the SAD variable and fall dummy variable will be shown to be statistically significant for almost all the indices we consider.) First we present Table 3 which provides an analysis of each index's average annual percentage return due to the SAD variable and due to the fall variable. For each index in our study we present in the first column of statistics the average annualized return due to our SAD measure. In computing the return due to SAD for a particular index, we calculate for each trading day the value of the SAD variable (which varies between zero and six for Sweden, for example, during the fall and winter, and which equals zero otherwise), multiply by that index's SAD variable estimate (presented in Tables 4A–4C), and adjust the value to obtain an annualized return. In the next column we present for each exchange the average annualized return due to the fall dummy variable. In calculating the return due to the fall dummy, we calculate for each trading day that country's fall dummy variable estimate (presented in Tables 4A–4C) multiplied by the value of the fall dummy variable (one during the fall, zero otherwise), then we adjust the value to obtain an annualized return. The final column presents the average annual percentage return for each index. One, two, and three asterisks

TABLE 3—AVERAGE ANNUAL PERCENTAGE RETURN DUE TO SAD AND DUE TO FALL DUMMY

Country	Annual return due to SAD	Annual return due to fall dummy	Unconditional annual return
United States: S&P 500	9.2***	−3.6**	6.3***
United States: NYSE	6.1*	−2.5*	9.2***
United States: NASDAQ	17.5***	−8.1***	12.5***
United States: AMEX	8.4***	−5.1***	8.4***
Sweden	13.5**	−6.9**	17.1***
Britain	10.3**	−2.3	9.6***
Germany	8.2*	−4.3**	6.5**
Canada	13.2***	−4.3**	6.1***
New Zealand	10.5**	−6.6**	3.3
Japan	6.9*	−3.7**	9.7***
Australia	5.7	0.5	8.8***
South Africa	17.5*	−2.1	14.6***

Notes: In calculating the average annual return due to SAD for a particular country, we determine for each trading day the value of the SAD variable (which varies between zero and six for Sweden, for example, during the fall and winter, and which equals zero otherwise), multiplied by that country's SAD variable estimate (from Table 4), then we adjust the value to obtain an annualized return. Similarly, in calculating the annual average return due to the fall dummy for a particular country, we determine for each trading day that country's fall dummy variable estimate (from Table 4) multiplied by the value of the fall dummy variable (one during the fall, zero otherwise), then we adjust the value to obtain an annualized return. In the case of the columns for the annualized returns due to the SAD and fall dummy variables, significance is based on t-tests on the parameter estimates from Table 4. In the case of the unconditional return column, significance is based on t-tests for a mean daily return different from zero.

* Significant at the 10-percent level, one-sided.
** Significant at the 5-percent level, one-sided.
*** Significant at the 1-percent level, one-sided.

[12] According to Ernst & Young (1998), the tax year commences on January 1 in the United States, Canada, Germany, Japan, and Sweden. The tax year starts on April 6 in Britain, on July 1 in Australia, on March 1 in South Africa, and on April 1 in New Zealand. For Britain, since the tax year ends on April 5, the tax-year dummy equals one for the last trading day before April 5 and the first five trading days starting on April 5 or immediately thereafter. The tax-year dummy is defined analogously for the other countries in the sample.

[13] All of the climate data (cloud cover, precipitation, and temperature) were obtained from the Climate Data Library operated jointly by the International Research Institute for Climate Prediction and the Lamont-Doherty Earth Observatory of Columbia University: ingrid.ldeo.columbia.edu. We are grateful to these organizations for making the data available.

indicate significance at the 10-, 5-, and 1-percent levels, respectively, based on one-sided hypothesis tests. For the annualized returns due to the SAD variable and the fall dummy, significance is based on t-tests on the corresponding coefficient estimates from estimating equation (5) (to be discussed below) upon which the calculations of the annualized returns are based. For the unconditional returns, significance pertains to t-tests on daily returns differing from zero.

There are some striking aspects of Table 3. First, the average annualized return due to SAD is positive in all countries, ranging from 5.7 percent to 17.5 percent. For the most part, countries at latitudes closer to the equator tend to have lower, less significant returns due to SAD than countries further from the equator. (In many cases, the return due to SAD exceeds the entire unconditional annual return.) Second, the average annualized return due to the fall dummy is negative in all countries except for Australia. Third, the positive return due to SAD combined with the negative return due to the fall dummy suggests that on balance the seasonally asymmetric effects of SAD are shifting returns from the fall to the winter.

Results from estimating equation (5) for each of our 12 indices appear in Tables 4A–4C. Names of all the parameters from equation (5) are indicated in the first column, and estimates for each market appear in the cells under each market's name. Below each parameter estimate is a heteroskedasticity-robust t-statistic.[14] In cases where a particular parameter was not estimated (ρ_1 and/or ρ_2 for some indices), a dash (—) appears. (We only used as many lagged depended variables as was required to eliminate residual autocorrelation up to the 1-percent level of significance. Tests for autocorrelation are discussed below.) One, two, and three asterisks indicate significance at the 10-, 5-, and 1-percent levels, respectively, based on one-sided hypothesis tests.

We see in Tables 4A–C that the SAD coefficient estimate is uniformly positive across all countries and is significant in all countries except one. The fall dummy coefficient estimate is

[14] The standard errors are calculated using a modification of Halbert White's (1980) standard error estimator suggested by James G. MacKinnon and White (1985) and recommended for its sampling distribution properties.

TABLE 4A—REGRESSION RESULTS FOR EACH OF THE U.S. INDICES

$$r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \mu_{Monday} D_t^{Monday} + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \mu_{Cloud} Cloud_t + \mu_{Precipitation} Precipitation_t + \mu_{Temperature} Temperature_t + \varepsilon_t$$

Panel A: Parameter Estimates (Heteroskedasticity-robust t-tests)

Parameter	S&P 500 41°N	NYSE 41°N	NASDAQ 41°N	AMEX 41°N
μ	−0.049	0.015	−0.017	0.051
	(−0.45)	(0.13)	(−0.11)	(0.47)
ρ_1	0.063***	0.151***	0.145***	0.269***
	(3.54)	(5.93)	(4.93)	(8.80)
ρ_2	−0.042***	—	—	—
	(−2.40)	—	—	—
μ_{Monday}	−0.209***	−0.124***	−0.256***	−0.280***
	(−9.50)	(−5.20)	(−7.50)	(−12.0)
μ_{Tax}	0.065	0.010	0.067	0.183***
	(1.14)	(0.14)	(0.72)	(2.71)
μ_{SAD}	0.038***	0.026*	0.071***	0.035***
	(2.43)	(1.61)	(2.96)	(2.34)
μ_{Fall}	−0.058**	−0.040*	−0.134***	−0.084***
	(−2.20)	(−1.40)	(−3.30)	(−3.20)
μ_{Cloud}	0.115	0.046	0.087	0.021
	(0.74)	(0.27)	(0.40)	(0.13)
$\mu_{Precipitation}$	−0.002	−0.001	−0.003	−0.002
	(−0.59)	(−0.21)	(−0.61)	(−0.84)
$\mu_{Temperature}$	0.003**	<0.001	0.003*	0.001
	(1.80)	(0.26)	(1.35)	(0.54)

Panel B: Diagnostics

R^2	0.011	0.027	0.033	0.091
AR(10)				
p-value	0.136	0.850	0.023	0.003

Notes: This table reports coefficient estimates from running the indicated regression for each of the four indices considered. Returns (r_t) are regressed on a constant (μ), lagged returns where necessary (one lag is required for all indices except the S&P 500, which requires two), a dummy for the trading day following the weekend (D_t^{Monday}), a dummy for the last trading day and first five trading days of the tax year (D_t^{Tax}), the SAD measure ($SAD_t = H_t - 12$ during fall and winter, 0 otherwise, where H_t = number of hours of night), a dummy for trading days in the autumn (D_t^{Fall}), percentage cloud cover ($Cloud_t$), millimeters of precipitation ($Precipitation_t$), and temperature in degrees Celsius ($Temperature_t$). All indices are value-weighted and do not include dividend distributions. Beneath each index's name, we indicate the latitude of the city in which the exchange is located.

In Panel A, we present parameter estimates with associated t-statistics in parentheses immediately below (calculated using heteroskedasticity-robust standard errors). For cases where particular parameters were not estimated, the relevant cells contain a dash (—). In Panel B, we present the R^2 for each regression as well as the p-value for a χ^2 test for autocorrelation up to ten lags.

* Significant at the 10-percent level, one-sided.
** Significant at the 5-percent level, one-sided.
*** Significant at the 1-percent level, one-sided.

TABLE 4B—REGRESSION RESULTS FOR EACH OF SWEDEN, BRITAIN, GERMANY, AND CANADA

$$r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \mu_{Monday} D_t^{Monday} + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \mu_{Cloud} Cloud_t + \mu_{Precipitation} Precipitation_t + \mu_{Temperature} Temperature_t + \varepsilon_t$$

Panel A: Parameter Estimates (Heteroskedasticity-robust t-tests)

Parameter	Sweden 59°N	Britain 51°N	Germany 50°N	Canada 43°N
μ	0.267*	0.231	0.097	−0.067
	(1.40)	(1.36)	(0.69)	(−0.50)
ρ_1	0.110***	0.061*	0.057***	0.153***
	(3.94)	(1.34)	(3.04)	(4.64)
ρ_2	—	—	—	—
	—	—	—	—
μ_{Monday}	−0.036	−0.117***	−0.149***	−0.131***
	(−0.76)	(−3.00)	(−4.80)	(−5.50)
μ_{Tax}	0.135	0.146*	0.165**	0.034
	(0.84)	(1.55)	(1.67)	(0.43)
μ_{SAD}	0.028**	0.030**	0.025*	0.052***
	(1.97)	(2.03)	(1.58)	(3.24)
μ_{Fall}	−0.113**	−0.036	−0.070**	−0.069**
	(−2.00)	(−0.80)	(−1.90)	(−2.10)
μ_{Cloud}	−0.374*	−0.271	−0.130	0.168
	(−1.30)	(−1.00)	(−0.53)	(0.63)
$\mu_{Precipitation}$	0.001	−0.017*	0.001	−0.003
	(0.09)	(−1.50)	(0.10)	(−0.88)
$\mu_{Temperature}$	−0.001	−0.001	0.001	0.002
	(−0.17)	(−0.30)	(0.36)	(1.16)

Panel B: Diagnostics

R^2	0.017	0.009	0.008	0.030
AR(10)				
p-value	0.131	0.218	0.029	0.019

Notes: This table reports coefficient estimates from running the indicated regression for each of the four indices considered. Returns (r_t) are regressed on a constant (μ), lagged returns where necessary a dummy for the trading day following the weekend (D_t^{Monday}), a dummy for the last trading day and first five trading days of the tax year (D_t^{Tax}), the SAD measure ($SAD_t = H_t - 12$ during fall and winter, 0 otherwise, where H_t = number of hours of night), a dummy for trading days in the autumn (D_t^{Fall}), percentage cloud cover ($Cloud_t$), millimeters of precipitation ($Precipitation_t$), and temperature in degrees Celsius ($Temperature_t$). All indices are value-weighted and do not include dividend distributions. Beneath each country's name, we indicate the latitude of the city in which the exchange is located.

In Panel A, we present parameter estimates with associated t-statistics in parentheses immediately below (calculated using heteroskedasticity-robust standard errors). For cases where particular parameters were not estimated, the relevant cells contain a dash (—). In Panel B, we present the R^2 for each regression as well as the p-value for a χ^2 test for autocorrelation up to ten lags.

* Significant at the 10-percent level, one-sided.
** Significant at the 5-percent level, one-sided.
*** Significant at the 1-percent level, one-sided.

TABLE 4C—REGRESSION RESULTS FOR EACH OF NEW ZEALAND, JAPAN, AUSTRALIA, AND SOUTH AFRICA

$$r_t = \mu + \rho_1 r_{t-1} + \rho_2 r_{t-2} + \mu_{Monday} D_t^{Monday} + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \mu_{Cloud} Cloud_t + \mu_{Precipitation} Precipitation_t + \mu_{Temperature} Temperature_t + \varepsilon_t$$

Panel A: Parameter Estimates (Heteroskedasticity-robust t-tests)

Parameter	New Zealand 37°S	Japan 36°N	Australia 34°S	South Africa 26°S
μ	−0.400	0.003	0.106	−0.273*
	(−0.73)	(0.02)	(0.48)	(−1.40)
ρ_1	—	—	0.089**	0.088***
	—	—	(1.94)	(3.63)
ρ_2	—	—	—	—
	—	—	—	—
μ_{Monday}	−0.204***	−0.040*	−0.038	−0.123***
	(−3.80)	(−1.40)	(−1.10)	(−3.00)
μ_{Tax}	−0.218*	0.009	0.125*	0.012
	(1.50)	(0.12)	(1.60)	(0.11)
μ_{SAD}	0.047**	0.037*	0.029	0.113*
	(1.70)	(1.55)	(0.89)	(1.62)
μ_{Fall}	−0.108**	−0.060**	0.007	−0.033
	(−2.20)	(−1.90)	(0.22)	(−0.89)
μ_{Cloud}	0.426	0.095	−0.328	0.137
	(0.56)	(0.58)	(−1.00)	(0.61)
$\mu_{Precipitation}$	0.001	−0.004	−0.005**	−0.001
	(0.43)	(−1.10)	(−2.20)	(−0.26)
$\mu_{Temperature}$	0.011*	−0.001	0.005	0.015*
	(1.48)	(−0.47)	(0.80)	(1.56)

Panel B: Diagnostics

R^2	0.010	0.002	0.010	0.010
AR(10)				
p-value	0.972	0.011	0.203	0.071

Notes: This table reports coefficient estimates from running the indicated regression for each of the four indices considered. Returns (r_t) are regressed on a constant (μ), lagged returns where necessary (New Zealand and Japan do not require lagged returns), a dummy for the trading day following the weekend (D_t^{Monday}), a dummy for the last trading day and first five trading days of the tax year (D_t^{Tax}), the SAD measure ($SAD_t = H_t - 12$ during fall and winter, 0 otherwise, where H_t = number of hours of night), a dummy for trading days in the autumn (D_t^{Fall}), percentage cloud cover ($Cloud_t$), millimeters of precipitation ($Precipitation_t$), and temperature in degrees Celsius ($Temperature_t$). All indices are value-weighted and do not include dividend distributions. Beneath each country's name, we indicate the latitude of the city in which the exchange is located.

In Panel A, we present parameter estimates with associated t-statistics in parentheses immediately below (calculated using heteroskedasticity-robust standard errors). For cases where particular parameters were not estimated, the relevant cells contain a dash (—). In Panel B, we present the R^2 for each regression as well as the p-value for a χ^2 test for autocorrelation up to ten lags.

* Significant at the 10-percent level, one-sided.
** Significant at the 5-percent level, one-sided.
*** Significant at the 1-percent level, one-sided.

negative in all countries except one and is significantly negative in all cases except three. Overall, this is consistent with a SAD-induced seasonal pattern in returns as depressed and risk-averse investors shun risky assets in the fall and resume their risky holdings in the winter, leading to returns in the fall which are lower than average and returns following the longest night of the year which are higher than average. Recall from Table 3 that the magnitude and significance of the SAD effect is broadly related to latitude: countries at higher latitudes (where the seasonal variation in daylight is more extreme) tend to experience larger, more significant returns due to the SAD effect relative to those closer to the equator.

Regarding other aspects of the estimation, we find the Monday dummy and tax-loss dummy are significant for many countries. The parameter estimates associated with cloud cover, precipitation, and temperature are typically insignificant. In Panel B of each table, we present the R^2 for each regression as well as the p-value for a χ^2 test for autocorrelation up to ten lags. In all cases, we fail to reject the null hypothesis of no residual autocorrelation at the 1-percent level, with the exception of the AMEX. An expanded model controlling for autocorrelation in the AMEX index produces qualitatively identical results.

B. *Trading Strategies*

The results in Tables 3 and 4A–4C suggest potential gains to employing a trading strategy based on the SAD effect. To explore this possibility, we provide an illustration of the returns earned by an investor from various trading strategies for a sample pair of countries, one from each hemisphere. We select for our example Sweden and Australia, each being one of the most extremely located countries in its hemisphere, and each having available roughly the same length of returns data (starting in the early 1980's). Consider first the benchmark "neutral" portfolio allocation strategy in which an investor in the early 1980's placed 50 percent of her portfolio in the Swedish index and 50 percent in the Australian index. Twenty years later, the average annual return to this neutral strategy would have been 13.2 percent (using annualized returns based on the daily returns shown in Table 2). Next, had the investor adopted a pro-SAD portfolio allocation strategy in which she reallocated 100 percent of her portfolio twice a year at fall and spring equinox, placing her money in the Swedish market during the Northern Hemisphere's fall and winter, then moving it into the Australian market for the Southern Hemisphere's fall and winter, her average annual return would have been 21.1 percent (which is 7.9 percent more than under the neutral strategy).[15] By comparison, had she instead allocated her portfolio across countries in order to act *against* the SAD effect, moving her money into the Swedish market for the Northern Hemisphere's spring and summer and then into the Australian market for the Southern Hemisphere's spring and summer, her average annual return would have been 5.2 percent (which is 8.0 percent less than she would have earned under the neutral strategy).

Had the investor been willing and able to assume short positions, she might have attempted to profit from the SAD effect by shorting the Swedish market during the Northern Hemisphere's spring and summer and going long in the Australian market during the same time (when it is fall and winter in the Southern Hemisphere), then going long in the Swedish market during the Northern Hemisphere's fall and winter while shorting the Australian market. The average annual return per dollar invested in this strategy would have been 15.9 percent. Of course, had she taken long and short positions in the two markets in a reverse pattern, acting against the SAD effect, her average annual return would have been −15.9 percent. Overall, we find that by adopting a pro-SAD strategy, the investor in our example would have realized relatively substantial excess returns, while trading against the SAD effect would have been costly.[16] Interestingly, for all

[15] The returns for all the trading strategies other than the neutral strategy are based on the six-month returns corresponding to the fall and winter or the spring and summer, as appropriate, for the index in question. For simplicity, we neglect transaction costs.

[16] In considering pro-SAD trading strategies across other countries, we found the following. Applying the pro-SAD portfolio allocation strategy, an investor would have enjoyed positive excess returns reallocating her funds between Australia and all Northern Hemisphere indices, as well as between New Zealand and all Northern Hemisphere markets except the United States. Pro-SAD trading strategies

the countries we consider, the volatility of returns does not vary appreciably across the spring/summer and fall/winter periods, suggesting that there is little difference in risk across the trading strategies we consider.

V. Robustness Checks

All of the detailed estimation results described in this section are provided in the Appendix (available from the authors).

A. *Maximum-Likelihood Model*

In the previous section, we addressed the issue of autocorrelation by introducing lags of the dependent variable, and we addressed the possibility of heteroskedasticity by using White (1980) standard errors. We have also estimated a maximum-likelihood model which jointly models the mean and variance of returns. We controlled for heteroskedasticity using the Sign-GARCH model of Lawrence R. Glosten et al. (1993) and produced robust *t*-tests using the robust (to heteroskedasticity and nonnormality) standard errors of Tim Bollerslev and Jeffrey M. Wooldridge (1992).[17] With the exception of some minor quantitative changes, overall the maximum-likelihood results are very similar to the results reported above. Though we typically find coefficients on the SAD variable and the tax-loss and fall dummies are slightly reduced in magnitude, we do still see large, economically meaningful effects due to SAD.

B. *Other Measures for SAD*

As previously discussed, theory does not specify the exact form that the SAD measure must take. Therefore, we considered some alternate measures including using the number of hours of night normalized to lie between 0 and 1, the number of hours of night normalized to lie between -1 and $+1$, and allowing the SAD measure to take on nonzero values through all four seasons. Broad qualitative statements that can be made about the economically significant magnitude, sign, and statistical significance of the SAD effect through the fall and winter are roughly the same across all measures we explored.

C. *SAD and Asymmetry Around Winter Solstice*

All of the results reported above were based on allowing for asymmetry around winter solstice by using a dummy variable set to equal one during trading days in the fall. We also explored an alternative parameterization, allowing the fall to differ from the winter by splitting the SAD measure into two separate regressors. (One regressor was set to equal the value of the SAD measure during the fall and zero otherwise. The other regressor was set to equal the value of the SAD measure during the winter and zero otherwise.) There was no need for a fall dummy variable in this case. We found no qualitative difference in results to those presented in this paper. With both types of parameterizations, we find evidence of the same asymmetric SAD effects.

We additionally explored the timing of breakpoints (around which point in time the fall/winter asymmetry would revolve), as well as whether we should allow for any asymmetry at all. Allowing for a breakpoint at winter solstice seemed best able to capture the asymmetry of the SAD effect. Results using different breakpoints or using no breakpoint produce broadly supportive results.

D. *Redefining the Tax-Loss Variable*

In the results presented above, the tax-loss dummy variable equals one for a given country when period *t* is in the last trading day or first five trading days of the tax year and equals zero otherwise, consistent with what other studies in the tax-loss literature have documented. Another possible specification is to define the

would have yielded a mix of positive and negative returns for reallocations between South Africa and Northern Hemisphere markets, perhaps due to the fact that many large South African companies are gold-producing companies which are cross-listed in London and New York. Detailed results on strategies based on all combinations of the markets we consider are available on the Web at www.markkamstra.com or from the authors on request.

[17] The Sign-GARCH model was selected because among commonly applied methods, it tends to work most reliably. See, for example, Robert F. Engle and Victor K. Ng (1993) and Donaldson and Kamstra (1997).

tax-loss dummy to equal one for all the trading days in the first month of the tax year. When this alternate specification is employed, the SAD effect is somewhat stronger and the tax-loss effect is somewhat weaker in significance.

VI. Market Segmentation and SAD Effects

To the extent that there is cross listing of stocks from, for example, Australia, that also trade in New York as American Depositary Receipts (ADRs) or in other forms, arbitrage would tend to dampen any potential SAD effects in the much smaller Southern Hemisphere markets. Nevertheless, we still find evidence of a SAD effect in the Southern Hemisphere despite any dampening that might be occurring. Also, if the international capital markets were fully integrated, there would be dampening of the SAD effect across the hemispheres: investors from the Northern Hemisphere would buy in the Southern Hemisphere at the very time that those in that hemisphere were selling, and vice versa. However, the evidence, as described by Maurice D. Levi (1997), Karen K. Lewis (1999), and others, suggests that markets are not fully integrated; there is a strong home-equity bias. Market segmentation is also supported by correlations between national savings and investment rates as shown by Martin Feldstein and Charles Horioka (1980): these correlations are higher than one would expect in an integrated international capital market. Furthermore, even if international capital markets were integrated, the dominant size of the Northern Hemisphere markets would mean that we would still expect to see a SAD effect (albeit that of the Northern Hemisphere).

VII. Conclusion

The preponderance of the evidence in this paper supports the existence of an important effect of seasonal affective disorder on stock market returns around the world. Specifically, even when controlling for the influence of other environmental factors and well-known market seasonals, we still find a large and significant SAD effect in every northern country we consider. In general the effect is greater the higher the latitude. Furthermore, evidence suggests the impact of SAD in the Southern Hemisphere is out of phase by six months relative to the north, as expected. Overall, results are robust to different measures to capture the effect of SAD, and do not appear to be an artifact of heteroskedastic patterns in stock returns.

Supporting our argument is the fact that daylight has been shown in numerous clinical studies to have a profound effect on people's moods, and in turn people's moods have been found to be related to risk aversion. SAD is a recognized clinical diagnosis, with recommended treatments including light therapy, medication, and behavior modification: sufferers are urged to spend time outdoors or take vacations where daylight and sunlight are more plentiful. Of course, we are not suggesting these treatments be applied to *influence* market returns. Rather, we believe that we have identified another behavioral factor that should not be ignored in *explaining* returns.

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