Winter Blues: Seasonal Affective Disorder (SAD) and Stock Market Returns

by

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Abstract

This paper investigates the role of seasonal affective disorder (SAD) in the seasonal time-variation of stock market returns. SAD is an extensively documented medical condition whereby the shortness of the day in fall and winter leads to depression for many people. Experimental research in psychology and economics indicates that depression, in turn, causes heightened risk aversion. Building on these links between the length of day, depression, and risk aversion, we provide international evidence that stock market returns vary seasonally with the length of the day, a result we call the SAD effect. Using data from numerous exchanges and controlling for well-known market seasonals, stock returns are shown to be significantly related to the amount of daylight through the course of the year. Patterns in the Northern and Southern 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. Overall, the economic magnitude of the SAD effect is large, comparable to that of the tax-loss effect in almost all the countries we consider.

"And God said, Let there be light;
and there was light.
And God saw that the light was good."

Genesis 1:3

Time-varying risk premia have been well documented in a wide range of financial settings including the term structure of interest rates, currency markets, futures markets, and stock markets. For example, see Kho [1996], Evans [1998], Campbell, Kazemi and Prasad [1999], and Roberds and Whiteman [1999]. Investigations of time-variation in risk premia have varied in their use of empirical methods such as nonparametric kernel estimation (see McCurdy and Stengos [1992]) and generalized method of moments (as shown by Zhou [1994]), statistical models including ARCH-in-mean (developed by Engle, Lilien and Robins [1987]) and asset pricing models such as the conditional CAPM and APT (see Kryzanowski, Lalancette and To [1997] and De Santis and Gerard [1997]). In this paper, we document a new seasonal pattern in stock market returns consistent with a time-varying risk premium associated with depression due to seasonal variations in the length of the day during the year.

Depression has been linked with Seasonal Affective Disorder, SAD, a condition that affects many people during short winter days. 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. We consider stock market index data from countries at various latitudes and on both sides of the equator and model differences in the seasonal variation of daylight across countries to capture the influence of changes in daylight on human sentiment, risk tolerance, and hence stock returns.

This paper is organized as follows. In Section 1, we discuss SAD, depression, and equilibrium market returns. In Section 2 we introduce the international datasets. In Section 3, we explain the construction of the variables intended to capture the influence of SAD on the stock market. Section 4 shows the significance of the SAD effect, comparing and contrasting it with the tax-loss selling effect. In Section 5, we discuss procedures that provide results robust to heteroskedasticity and non-normality of returns, alternate specifications of the tax-loss selling effect, and additional measures of SAD. Section 6 considers SAD in the context of segmented versus integrated capital markets. Section 7 provides conclusions.

1 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 Rosenthal [1998], the recurrent problems associated with 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.[1]

SAD is clinically defined as a form of major depressive disorder. See, for example, Bagby *et. al.* [1996], Leonhardt *et. al.* [1994], Avery *et. al.* [1993], and Meesters *et. al.* [1993]. 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 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.[2] For those affected, the annual onset of SAD symptoms can occur as early as September, around the time of autumn equinox. See Dilaver [1990], for example.

Experimental research in psychology has documented a direct link between depression and heightened risk aversion. The psychology literature establishes this link by providing measures of risk-taking propensity including a scale of "sensation-seeking" tendencies. These measures are extensively documented as reliable measures of risk-taking in financial decision-making settings.[3] The experimental evidence shows that depression lowers scores on these scales of risk-taking propensity.[4] That is, 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 implication is a causal relationship between seasonal patterns in length of day and market returns.

Studies on individuals at extreme latitudes, including work by Palinkas, Houseal, Rosenthal [1996] and Palinkas and Houseal [2000], suggest the depressive effects of SAD and hence risk aversion are 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 SAD and the winter blues brought on by short days lead to relatively lower returns in the fall and relatively higher returns in the winter.

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. The length of the night during the course of the year peaks in the Northern Hemisphere on the winter solstice, December 21st, reaches a trough on the summer solstice, June 21st, and follows a path that approximates a sine function passing through these two values. In the Southern Hemisphere, the sine curve is 6-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 from the equator, *i.e.*, the larger is the latitude north or south. Figure 1 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 1 reflect the length of night for the latitude at which a country's stock exchange is located, rounded to the nearest degree.

1.1 Comparing SAD and Sunshine Effects

A related literature investigates the influence of sunshine on market returns. As argued by Saunders [1993] and Hirshleifer and Shumway [2001], the number of hours of sunshine affects peoples' moods and hence also possibly market returns.[6] The amount of sunshine is affected by cloud cover as well as the number of hours of daylight, and indeed, Saunders 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. Hirsleifer and Shumway [2001] present further evidence for a sunshine effect in a study of 26 international stock markets. Both of these studies of sunshine consider weather at the level of cities in which the markets are located. Our study of daylight is complementary, though there is an important distinction between the two streams of research. The Saunders [1993] and Hirshleifer and Shumway [2001] papers posit that the weather in the city where the exchange is located will influence market returns through the mood of traders on the floor of the exchange in that particular city. Our paper posits that the effect of SAD on all investors in the hemisphere influences returns, and since the number of hours of daylight varies similarly across regions, countries, and throughout the hemisphere, whether an individual investor is in New York or Los Angeles, her mood would be expected to manifest similarly in market returns through the course of the year.

2 Market Returns Data & Measuring the Tax-Loss Selling Effect

With many of the shortest days being in January in the Northern Hemisphere (and July in the Southern Hemisphere) an obvious question is whether the tax-loss effect, which often occurs in January in the Northern Hemisphere and occurs in July in Australia, is at least partially an element of a seasonality in returns related to SAD.[7] The daily stock index return data used in this study to investigate this possibility are outlined in Table 1. The eight indices were selected to span different latitudes and the two hemispheres.[8] With the exception of New Zealand's Capital 10 index (which we include to supplement Australia's representation of the Southern Hemisphere), we examine large-capitalization, broad-based indices, including the largest exchange among the far northerly markets (Stockholm, Sweden) and the largest exchange in the Southern Hemisphere (Sydney, Australia).[9] With the exception of the CRSP equal-weighted index, we study all value-weighted indices. By intentionally excluding more small-cap or equal-weighted indices, we bias our study *against* finding evidence of SAD, since investors' actions based on changes in risk aversion are less likely to be detected in relatively safer, large stocks.

For the case of the United States, we study both the value-weighted and equal-weighted CRSP indices. Consideration of both weightings allows us to see whether differences exist in the magnitude of the SAD effect under the two weightings as has been documented in the tax-loss literature, where stronger effects are found using equal-weighted returns. The United States returns include dividend payments. Results based on these data were compared to (unreported) results using the CRSP index returns excluding dividends and there were no important differences.[10] For countries where dividend payments take place on an annual basis, with significant clustering within the year, excluding dividends can lead to serious problems.[11] Fortunately, dividend clustering is not a problem for any of the countries we consider, and hence we do not expect excluding dividends for those countries adversely effects results.

Table 2 displays simple summary statistics for the raw data used in this study, the daily percentage returns for two indices in the United States, and an index for each of Canada, Britain, Germany, Sweden, Australia, and New Zealand. Directly below the name of each country is the period over which the returns were collected. The first column of statistics lists the number of observations available, ranging from a low under 3,000 for New Zealand to a high over 9,000 for the United States indices. The second column of statistics is the daily percentage mean return (excluding cash payments for all indices except those in the United States). The mean is of the same order of magnitude for all of the indices, ranging from about 0% to 0.07%. The standard deviation of the daily returns varies across countries, with New Zealand being the most volatile (unconditionally) at 1.22% and the United States equal-weighted the least volatile, at 0.68%. The largest single-day drop, a decline exceeding 28%, was experienced in Australia during the October 1987 crash. The largest single day gains ranged from 6.63% to 10.63%. All of the return series are strongly skewed to negative returns, and 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 Figure 2. This figure plots the monthly means of the daily percentage returns averaged across all seven value-weighted indices. Prior to averaging the returns the Australian and New Zealand data are shifted six months to adjust for the difference in seasons across the hemispheres. Thus month 1 represents the first month following winter solstice (the longest night of the year), January in the Northern Hemisphere and July in the Southern Hemisphere. The graph shows that while indeed the "month 1" returns (in winter) are the largest monthly returns, speaking very roughly there is an indication in the data of some sort of annual cycle: monthly returns over the year follow an approximate "U" shape. The raw data suggest that "month 1" may be an extreme point on a seasonal cycle. While these summary statistics are interesting, it is essential to note that they are unconditional results and do not control for other effects which may be in the data such as Monday effects, tax-loss selling effects, autocorrelation, and so on. Figures 3 and 4 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 means for the United States equal-weighted index (which, as the only equal-weighted index, was not included in the aggregate data used to create Figure 2), the United States value-weighted index, Canada, and Britain. Panels A through D of Figure 4 plot the monthly mean returns for Germany, Sweden, Australia, and New Zealand respectively. While the average annual patterns shown in the individual plots vary somewhat, they uniformly show strong mean returns in month 1, the month following the longest night of the year. The most extreme of these is the United States equal-weighted where the mean monthly return is over 0.3% in January. Broadly speaking, the returns drop thereafter, flatten out through the spring and summer, then decline in the autumn and start their annual rise again. The Southern Hemisphere exchanges, unconditionally at least, do not follow the same pattern in the fall, though less striking seasonal patterns may be unsurprising in the exchanges located closest to the equator.

Now we consider the tax-loss selling effect for the individual countries, estimated with a regression model following a conventional specification, including a lagged return variable to deal with autocorrelation, and dummy variables to capture the Monday effect and the tax-loss effect. The model is estimated as follows:[12] [13]

$$r_t = \mu + \rho r_{t-1} + \mu_{Mon} D_t^{Mon} + \mu_{Tax} D_t^{Tax} + \epsilon_t \tag{1}$$

where r_t is the period t return for a given country's index, D_t^{Mon} is a dummy variable which equals 1 when period t is the trading day following a weekend (usually a Monday) and 0 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 and 0 otherwise, and ϵ_t is a disturbance term.[14]

Table 3 shows results based on this model, indicating for each country the tax-loss dummy coefficient estimate and corresponding t-statistics and p-values. (Note that in this table, and in the rest of the paper, Australia and New Zealand returns are *not* shifted in the manner they were for Figures 2 and 4.) P-values below $\alpha\%$ reject, with $\alpha\%$ confidence, the null hypothesis that there is no tax-loss selling effect in favor of the alternative hypothesis that there is a tax-loss effect. Examining the p-values, we find a statistically significant tax-loss effect for all of the markets studied except Britain. The largest and most significant tax-loss effect occurs for the equally-weighted CRSP index in the United States, where the coefficient estimate is almost 0.4% and the p-value is less than 0.001. The magnitude of this effect, 0.4%, is large relative to the average daily return of only 0.075% for the equal-weighted CRSP. Roughly 13% of the entire year's return occurs in the 6-day period covered by the tax-loss dummy.[15] In what follows, we demonstrate that SAD accounts for a seasonal pattern in returns even after controlling for the tax-loss effects that appear in Table 3, and the economic magnitude of this effect is as large as or larger than that of the tax-loss effect.

3 Measuring the Effect of SAD

There is substantial variation in the amplitude of the the length-of-night cycle in different countries. Countries at extreme latitudes, such as Sweden, experience great variability relative to locations closer to the equator, such as Australia. Since theory does not provide an exact specification for capturing the impact of SAD on returns, we consider several alternative measures. One of these measures is introduced in this section. In Section 5 we discuss the similarity of results that arise using other measures.

The measure introduced in this section focuses on capturing the influence of SAD on returns during the fall and winter since SAD predominantly affects individuals during these two seasons. Variation in the amount of daylight through the spring and summer months is not believed by medical professionals to have a systematic effect on individuals' moods. Again, in Section 5, we discuss alternate specifications that allow for SAD-related effects through all four seasons. Results obtained using such specifications are virtually identical to those presented in this Section.

3.1 The Sine Wave Measure

We model the seasonal pattern in the length of night over the year using a sine approximation:

$$\text{SINE} = \begin{cases} 1 - \frac{\left(\sin\left(\pi \frac{julian}{182.5}\right)+1\right)}{2} & \text{in the Northern Hemisphere} \\ \frac{\left(\sin\left(\pi \frac{julian}{182.5}\right)+1\right)}{2} & \text{in the Southern Hemisphere} \end{cases} \tag{2}$$

where "$julian$" is a variable that ranges from 1 to 365 (366 in a leap year), representing the number of the day in the year. $Julian$ equals 1 for January 1, 2 for January 2 and so on. The behavior of this function in each hemisphere is shown in Figure 5. The sine wave for each hemisphere represents simple monotonic transformations of the length of night functions for each country, some of which were shown in Figure 1. For each country, we define the "sine wave measure" of SAD, denoted SAD_t, as follows:[16]

$$SAD_t = \begin{cases} \text{value of Equation (2)} & \text{in fall and winter (Sept. 21 - March 20)} \\ 0 & \text{in spring and summer (March 21 - June 20).} \end{cases} \tag{3}$$

By definition, this variable is invariant to latitude within either hemisphere – the value of SAD_t through the year is the same for all countries within a hemisphere. Since SAD_t tracks the length of night through the fall and winter, and since the depression associated with longer nights is related to increases in risk aversion, we expect this variable to be positively related to stock returns. That is, we expect investors facing heightened risk aversion to require relatively higher returns to induce them to hold risky assets over a given period.

3.2 Asymmetry Around Winter Solstice

There are a number of reasons for expecting an asymmetric response to the length of night before winter solstice relative to after. First, as mentioned in Section 1, results from psychology indicate the impact of SAD on human sentiment in the fall may well differ from that in the winter. Second, the trading activity of a SAD-affected investor may imply asymmetric patterns in equity returns before winter solstice relative to after in the following way. If investors become more risk averse at $t = 1$ (the onset of fall) and then return to "normal" levels of risk aversion at $t = 3$ (the end of winter), higher compensating returns for holding the asset between those points in time are generated by an initial relative price decline at $t = 1$. That is, if P_1^* is the expected price at $t = 1$ in absence of any change in risk aversion, we should observe an actual price P_1 which is *below* P_1^*. That is, with the onset of heightened risk aversion associated with SAD, prices are lower than they would be otherwise. After levels of risk aversion return to their previous, non-SAD influenced levels at the end of winter, at $t = 3$, prices return to their expected levels, reflected by P_3^*. That is the actual price $P_3 = P_3^*$. The implication is that investors who bought the risky asset prior to $t = 1$, say in summer, and sold at the onset of fall, $t = 1$, would experience lower than average returns. Investors who bought the risky asset at $t = 1$ and sold at the end of winter, at $t = 3$, would experience higher than average returns.

In order to allow for an asymmetric affect in the fall relative to the winter, we introduce a dummy variable for days of the year which are in the fall season:[17]

$$D_t^{Fall} = \begin{cases} 1 & \text{for trading days in the fall (Sept. 21 - Dec. 20)} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

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.

4 Influence of the SAD Effect

An obvious way to test for a SAD effect is to regress returns on all variables thought to be relevant, including those related to SAD. We consider such an approach later in this section. We start, however, with a particularly stringent test of the SAD effect by first removing known seasonals from the data, specifically by regressing returns on a tax loss dummy, a Monday dummy and lagged returns. (That is, we start by estimating Equation (1), the regression which yielded the results shown in Table 3.) This expunges well-known effects from returns. We collect the residuals, $\hat{\epsilon}_t$, from this regression and then regress them on the dummy for the fall season and the SAD measure to determine whether SAD explains anything that remains. That is, we estimate:

$$\hat{\epsilon}_t = \alpha + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \eta_t \tag{5}$$

where η_t is a disturbance term. If coefficient estimates on the SAD variable are significant, notably after removal of the extensively documented tax-loss and other effects, then what we are calling the SAD effect is a seasonal pattern in its own right.

The results of this stringent test of SAD appear in Table 4. The first column of statistics shows the results for the SAD coefficient, and the second column contains results for the fall season dummy variable coefficient. In each cell, the top figure is the coefficient estimate, the middle figure is the t-statistic, and the bottom figure is the p-value associated with the t-statistic. The first notable aspect of the results in Table 4 is that all eight indices have positive coefficients on the SAD variable, and seven of these are significant. The same seven indices have significantly negative coefficients on the fall dummy variable. Consider the "net effect" of the SAD and fall variables, defined as the sum of the SAD coefficient estimate times the value of the SAD variable and the fall dummy coefficient estimate times the value of the fall dummy, *i.e.* $\hat{\mu}_{SAD} SAD_t + \hat{\mu}_{Fall} D_t^{Fall}$. Notice that for much of the fall (the period for which the fall dummy equals 1 and SAD_t ranges from a low of 0 on September 21 to a high of 1 on December 21), the net effect is negative for seven of the eight indices. For instance, for the United States equal-weighted index, $\hat{\mu}_{SAD}$ equals 0.077 and $\hat{\mu}_{Fall}$ equals -0.075. The net effect does not become positive until just before December 21, when the value of SAD_t approaches 1. The net effect stays positive for the duration of the winter because, of course, $D_{Fall} = 0$ for that period. For New Zealand, $\hat{\mu}_{SAD}$ equals 0.107 and $\hat{\mu}_{Fall}$ equals -0.085. Given these values, the net effect for New Zealand does not become positive until roughly late May (equivalent to late November in terms of Northern Hemisphere seasons). Results are similar for all countries considered except Australia.

The sine wave measure of SAD allows for comparison of magnitudes of the coefficient estimates across countries (as the SAD measure itself does not vary with latitude within either hemisphere). We expect countries at more extreme latitudes to have larger SAD coefficient estimates using this measure, and this is roughly what we find.[18] The two countries located at the highest latitudes, Britain and Sweden, have the largest coefficient estimates. The country closest to the equator, Australia, has the smallest (and the only insignificant value). Comparing the indices, we find that Canada, which is at a higher latitude, has a larger effect than either of the United States' indices.

The incidence of the SAD effect shown in Table 4 is consistent with the view that, due perhaps to a greater degree of risk aversion as people suffer from winter blues, returns in the fall are lower than average and returns following the longest night of the year are higher than average. Note that this effect appears in spite of having previously controlled for the tax-loss effect: we are regressing the SAD variable against the residuals from a model that has already removed the tax-loss selling effect. Using this two-stage test which is biased against finding the SAD effect, it is compelling that we nevertheless find such strong SAD effects for so many countries. For example, it was previously mentioned in reference to Table 3 that for the United States equal-weighted index, the tax-loss dummy coefficient of 0.4% represents about 13% of that market's annual returns. Yet the SAD measure (which captures effects over months including January) remains extremely significant and economically very large. The SAD coefficient is 0.077% for the case of the United States equal-weighted index, implying that on the longest night of the year, when the SAD variable takes on a value of 1, the portion of the daily return due to SAD is as large in magnitude as the average daily return of 0.075% for that index (from Table 2).

Note that for the United States, the SAD coefficient for the equal-weighted index is slightly greater than that of the value-weighted index (in terms of both magnitude and statistical significance).[19] This conforms with our findings for the tax-loss effect which, as Table 3 shows, is larger and more significant for the equal-weighted index (a finding which has been extensively documented in the tax-loss literature cited earlier). This is consistent with the SAD effect having a greater influence on smaller, riskier firms.

Let us now consider another way of testing for the SAD effect, allowing the tax-loss dummy and the SAD measure to simultaneously pick up effects in a single regression framework. We conduct a single regression for each country, regressing returns on lagged returns, a dummy variable for a tax-loss effect, a Monday dummy, the SAD measure, and the fall dummy. In this way, the SAD effect has to "compete" with the tax-loss effect for significance. Specifically, we estimate:

$$r_t = \mu + \rho r_{t-1} + \mu_{Mon} D_t^{Mon} + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \epsilon_t \tag{6}$$

Results for this estimation appear in Table 5, indicating for each country the coefficient estimate for the SAD_t variable, the fall dummy, the tax-loss dummy, and the corresponding t-tests and p-values. Once again all eight indices have positive coefficients on the SAD variable, and seven of the eight are significant at the 5% level or better. The same seven indices have significantly negative fall dummies. Once again, the net effect of the SAD variable and the fall dummy is negative through much of the fall and, of course, positive through the winter. This is consistent with a SAD-induced seasonal pattern in returns as depressed and risk averse investors sell off risky assets in the fall and resume their risky holdings in the winter. The magnitude of coefficient estimates for the SAD variable across countries are again broadly in conformity with patterns of daylight around the world, with magnitudes larger for countries at higher latitudes, like Sweden and Germany, and smaller for countries closer to the equator, like Australia and New Zealand. Again, the only insignificant SAD coefficient is observed in Australia. Notice that for the United States equal-weighted index the total effect of SAD during the winter is equal to about half the return generated during that 3-month period, and this amounts to about 15% of the total year's return for this index, making it comparable in magnitude to the annual effect from tax-loss selling (13%).[20] Similarly, the returns arising due to the SAD effect in winter exceed those arising from the tax-loss effect in all other indices considered except Australia.

It is worth noting that the SAD measure and the tax-loss dummy variable follow very different patterns. Recall that the SAD measure is an oscillating variable during the fall and winter while the tax-loss effect is captured by a simple 0/1 variable. The SAD variable is declining sharply over the month of January, while the tax-loss variable remains fixed at 1 for 6 trading days around the start of the tax year in those countries where the tax year commences on January 1. Similarly, in other months of the fall and winter the SAD measure continues to vary while the tax-loss dummy remains constant at 0 (or takes on a value of 1 for the beginning of the July or April tax-year for the case of Australia, New Zealand and Britain). Indeed, the correlation coefficient for the SAD_t variable and the tax-year variable is less than 0.3 for all countries. To the extent that the small degree of correlation might lead to problems associated with multicollinearity, the results shown in Table 4 avoid such problems by first controlling for the tax-loss effect and then testing for the SAD effect in the residuals.

5 Robustness Checks

5.1 Controlling for ARCH

A well-known feature of virtually all stock market return series is autoregressive conditional heteroskedasticity (ARCH) effects. The series we consider are typical in this respect, implying standard inference may be invalidated. Thus, in order to demonstrate that the significance of the SAD effect is not an artifact of inappropriate standard error estimates based on OLS, we controlled for heteroskedasticity and produce robust t-tests using the Sign-GARCH(1,1,1) model of Glosten, Jagannathan and Runkle [1993] (GJR) and Bollerslev Wooldridge [1992] robust (to heteroskedasticity and non-normality) standard errors.[21] The (unreported) results are available from the authors on request. With the exception of some minor quantitative changes, discussed below, overall the qualitative nature of the ARCH results is very similar to the results reported above. We typically find coefficients on the SAD variable and the tax-loss and fall dummies are slightly reduced in magnitude. We do, however, still see large, economically meaningful effects due to SAD, and the proportion of the annual return that can be attributed to SAD is again comparable in size to that arising due to the tax-loss effect. In fact the magnitude of the SAD coefficient is such that the SAD effect still constitutes about 10 to 20 percent of the entire year's returns in all the countries except Australia. The Bollerslev Wooldridge robust standard errors used to assess statistical significance of coefficient estimates are well-known to be conservative, tending to produce insignificant results. Yet the SAD variable remains significant in six of the indices, with only Germany and Australia showing a lack of significance. The tax-loss dummy is negative and insignificant for the United States value-weighted index and for Canada and is reduced in magnitude for the United States equal-weighted index and New Zealand.

5.2 Other Measures for SAD

As previously discussed, theory does not specify the exact form that the SAD measure must take. Therefore, we considered several measures in addition to those already examined. A natural choice to directly capture the variation is simply to take the number of hours of night, denoted H and defined as the time from sunset to sunrise. We can determine the number of hours of night using standard approximations from spherical trigonometry.[22] A second alternative was the actual number of hours of night normalized to lie vary around zero by deducting 12, that is H-12. A third was the actual number of hours of night normalized to lie between 0 and 1. We also explored specifications that permitted variations in daylight through the spring in summer to influence returns. In all cases, the regression results were similar to those discussed above for various measures of SAD. Broad qualitative statements that can be made about the economically significant magnitude, sign and statistical significance of the effect through the fall and winter are roughly the same across all measures.

5.3 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 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 equal 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 an 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. The most striking difference is that some of these measures picked up statistically significant, albeit weak, SAD effects for Australia. All of these results are available from the authors on request.

5.4 Re-defining the Tax-Loss Variable

For the results presented in the text, the tax-loss dummy variable was set to one for a given country when period t is in the last trading day or first five trading days of the tax year and 0 otherwise, consistent with what other studies in the tax-loss literature have documented. Another possible specification is to define the 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, both the SAD and tax-loss effects are similar in magnitude, albeit both somewhat weaker in significance. When both specifications of the tax effect are employed simultaneously, results are also similar.

6 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 some evidence of an 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 Levi [1997], 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 Feldstein and 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).

7 Conclusions

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 after removing the well-known and extensively documented tax-loss selling effect from returns, which occurs in many cases in January when the SAD effect is likely to be particularly severe in the Northern Hemisphere, we still find a significant SAD effect in every northern country we consider. Furthermore, evidence suggests the impact of SAD in the southern hemisphere is out of phase by six months relative to the north, as expected. We find a significant SAD effect in the southern hemisphere's winter and fall for New Zealand, but support for SAD is limited in Australia, the country closest to the equator. 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. Further, the results are apparent in spite of the almost exclusive use of large-capitalization indices, which biases our study against the finding of a SAD effect relative to smaller-cap markets. The magnitude of the SAD effect is large, with returns due to SAD in the winter exceeding those due to tax-loss selling in almost all the countries we consider. Taken as a whole, the results in this paper represent powerful support for the role that daylight plays in stock returns through its impact on risk aversion through the course of the year.

Supporting our argument is the fact that daylight has been shown in numerous clinical studies to have a profound effect on people's moods. Indeed, 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.

Promising corroborating results have been found within markets for relatively riskless assets in a preliminary study by Kamstra, Kramer and Levi [2001]. Specifically, they find that returns on bonds demonstrate an annual seasonal cycle which is 6 months out of phase relative to the SAD effect documented in markets for risky assets. That is, evidence suggests that when SAD-affected investors are seemingly shunning risky stock, they are buying relatively safer assets, and *vice versa*. This presents a promising agenda for future research into ways in which the behavior of individuals influences financial markets.

Endnotes

[1]For example, the frequency of SAD in northern Canada is documented by Williams and Schmidt [1993]. The incidence of SAD in Italy is discussed by Faedda *et. al.* [1993]. There is even evidence, from the Mayo Clinic [1998], 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. Similarity of frequency at extreme latitudes has led to suggestion of a "ceiling effect", with a plateau in the SAD effect above a certain latitude. See Lam [1994].

[2]Mayo Clinic *op. cit.*

[3]See, for instance, Horvath and Zuckerman [1993], Tokunaga [1993], and Wong and Carducci [1991].

[4]See, for instance, Carton *et. al.* [1995], Carton *et. al.* [1992], and Marvel and Hartman [1986].

[5] For further details on the impact of the marginal trader on market equilibria, see the classic papers by Hicks [1963] and Bierwag and Grove [1965], as well as the appendix "The Equilibrium Prices of Financial Assets" by Van Horne [1984].

[6]The effect of sunshine in self-assessment of moods is discussed by by Persinger [1975]. In addition, Howarth and Hoffman [1984] have shown that skepticism, defined as having a "cynical doubting outlook", is inversely related to sunshine, and that out of eight weather and ten mood variables, hours of sunshine is the only significant predictor of optimism scores.

[7]A summary of the earlier literature on the tax-loss selling effect can be found in Thaler [1987]. Papers published since Thaler's summary include Athanassakos and Schnabel [1994], Bhardwaj and Brooks [1992], Jones, Lee, and Apenbrink [1991], Kramer [1994], and Ligon [1997].

[8]In addition to the indices specified in Table 1, we also considered the S&P 500 index in the United States, as well as two other Swedish indices. The results for these indices are qualitatively the same as for those presented and are omitted for the sake of brevity.

[9] Other markets were considered but were rejected due to the lack of a sufficiently long time series, the presence of hyper-inflation, the small capitalization of the exchange, or the over-representation of a particular sector within the market.

[10]These results are available from the authors on request.

[11] Jeremy Siegel [1998] reports that for the United States of the 7% per year compounded annual real return on stocks, the dividend yield is about 4.5% and the real capital gain is about 2.5%. When using arithmetic averages of nominal returns on an equal-weighted

index, the dividend yield will be a smaller proportion of the average daily total return. In general, however, there is a severe misconception today regarding the relative importance of dividends and capital gains in historical returns. We thank the referee for pointing this out.

[12]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, Akgiray [1989], Donaldson and Kamstra [1997] and Pagan and Schwert [1990]. Seasonality in stock returns is explored in a wide range of papers including Chen, Roll and Ross [1986], Chang and Pinegar [1989, 1990] and Bouman and Jacobsen [2000]. There are numerous papers that study seasonal stock market effects as related to tax-loss selling, including Brown, Keim, Kleidon and March [1983], Tinic and West [1984], Kato and Schallheim [1985], and Ritter [1988].

[13]According to Ernst & Young [1998], the tax year commences on January 1 in the United States, Canada, Germany and Sweden. The tax year starts on April 6 in Britain, on July 1 in Australia, and on April 1 in New Zealand.

[14]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. For Australia, the tax-year dummy equals one for the last trading day in June and the first five trading days in July. Similarly, for New Zealand, the tax-year dummy equals one for the last trading day in March and the first five trading days in April.

[15]With a coefficient of approximately 0.4% applied to the 6 tax-loss days, the average accumulated tax-loss effect is roughly 2.4%. With an average daily return for the United States equal-weighted index of 0.075% (from Table 2) applied over approximately 250 trading days per year, the average annual return is 18.75% over July 1962 to December 1999. Thus the average tax loss effect represents $\frac{2.4\%}{18.75\%} \approx 13\%$ of the average annual return for this index.

[16]Note we assume autumn equinox takes place on September 21 in all countries every year. The actual timing can vary between September 20 and 23. We assume spring equinox takes place on March 21 in all countries every year. The actual timing can vary between March 20 and 22.

[17]We assume winter solstice takes place on December 21. The actual timing varies between December 20 and 23.

[18]Recall that for each country, we use the latitude at which the corresponding stock exchange is located.

[19]The difference across the equal- and value-weighted indices is even greater under the alternative specifications we discuss in Section 5.

[20]Using the average value of the SAD coefficient during the winter period, 0.5, and the SAD coefficient value of 0.09%, the average daily return accruing due to SAD during the approximately 62.5 trading days in winter is $0.5 \cdot 0.09\% \cdot 62.5 = 2.8\%$. This constitutes about 15% of the total annual return of 18.75% for this index.

[21]This specification was selected because among commonly applied methods, it tends to work most reliably. See, for example, Engle and Ng [1993] and Donaldson and Kamstra [1997].

[22]To calculate an estimate of the number of hours of night at latitude δ we first need the sun's declination angle, λ: $\lambda = 0.4102 \cdot sin\left[(\frac{2\pi}{365})(julian - 80.25)\right]$ where "$julian$" again represents the number of the day in the year. We can then calculate the number of hours of night as:

$$H = \begin{cases} 24 - 7.72 \cdot arcos\left[-tan(\frac{2\pi\delta}{360})tan(\lambda)\right] & \text{in the Northern Hemisphere} \\ \\ 7.72 \cdot arcos\left[-tan(\frac{2\pi\delta}{360})tan(\lambda)\right] & \text{in the Southern Hemisphere} \end{cases}$$

where "$arcos$" is the arc cosine.

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Table 1
Daily Stock Index Return Data
with Corresponding Cities and Latitudes

Country	Index	City	Latitude
United States	NYSE CRSP Equal-Weighted	New York	41° N
United States	NYSE CRSP Value-Weighted	New York	41° N
Canada	TSE 300	Toronto	44° N
Britain	FTSE 100	London	51° N
Germany	DAX 100	Frankfurt	50° N
Sweden	Veckans Affärer	Stockholm	59° N
Australia	All Ordinaires	Sydney	34° S
New Zealand	Capital 10	Auckland	37° S

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

Table 2
Daily Percentage Return Summary Statistics for Each Index

Country & Period	# of Obs.	Mean	Standard Deviation	Min	Max	Skew	Kurtosis
United States EW 62/07/03-99/12/31	9442	0.075	0.68	-10.48	6.94	-1.11	16.98
United States VW 62/07/03-99/12/31	9442	0.051	0.82	-17.17	8.67	-1.12	26.22
Canada 69/01/01-98/12/17	7,551	0.023	0.79	-10.29	9.88	-0.77	17.00
Britain 84/01/02-98/12/18	3,790	0.046	0.96	-13.03	7.60	-1.19	17.65
Germany 73/01/01-98/12/17	6,556	0.028	1.04	-13.46	7.28	-0.80	11.31
Sweden 82/09/14-99/11/04	4,296	0.073	1.15	-8.99	9.78	-0.27	7.95
Australia 80/01/01-99/11/03	5,029	0.034	1.00	-28.76	6.63	-5.24	142.46
New Zealand 88/06/30-99/11/17	2,865	-0.001	1.22	-15.45	10.63	-0.57	14.07

Note: All indices are value-weighted (VW) except the United States equal-weighted (EW). The United States EW and VW index return series include dividend distributions while all other index return series do not.

Table 3
Regression Results from Base Model
With Tax-Year Dummy

$D_t^{Mon} = 1$ on first trading day following weekend

$D_t^{Tax} = 1$ on last and first five trading days of tax year

$$r_t = \mu + \rho r_{t-1} + \mu_{Mon} D_t^{Mon} + \mu_{Tax} D_t^{Tax} + \epsilon_t$$

Country	$\hat{\mu}_{Tax}$ (t-test) (p-value)
United States EW	0.392*** (9.25) (<0.001)
United States VW	0.087* (1.58) (0.057)
Canada	0.103** (1.74) (0.041)
Britain	0.077 (0.76) (0.224)
Germany	0.203*** (2.40) (0.008)
Sweden	0.327*** (2.86) (0.002)
Australia	0.147* (1.61) (0.054)
New Zealand	0.168** (1.98) (0.024)

Note: Tax-year dummy variables were included for all countries. The variable equals one for the last trading day and the first five trading days of the tax year and equals zero otherwise. The tax year starts January 1 for all countries except Britain where the tax year starts April 6, Australia where the tax year starts July 1, and New Zealand where the tax year starts April 1.

* Significant at the 10% level, one-sided test
** Significant at the 5% level, one-sided test
*** Significant at the 1% level, one-sided test

Table 4
Regression Results from Regressing
Base Model Residual ($\hat{\epsilon}_t$) on SAD_t and D_t^{Fall}
$SAD_t =$ value of Equation (2) during winter and fall
$D_t^{Fall} = 1$ during fall
$\hat{\epsilon}_t = \alpha + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \eta_t$

Country	$\hat{\mu}_{SAD}$ (t-test) (p-value)	$\hat{\mu}_{Fall}$ (t-test) (p-value)
United States EW	0.077*** (4.07) (<0.001)	-0.075*** (-4.5) (<0.001)
United States VW	0.067*** (2.71) (0.003)	-0.039** (-1.8) (0.035)
Canada	0.093*** (3.47) (<0.001)	-0.062*** (-2.6) (0.004)
Britain	0.133*** (2.86) (0.002)	-0.089** (-2.2) (0.014)
Germany	0.070** (1.82) (0.035)	-0.066** (-2.0) (0.025)
Sweden	0.139*** (2.64) (0.004)	-0.118*** (-2.6) (0.004)
Australia	0.014 (0.35) (0.365)	0.022 (0.60) (0.274)
New Zealand	0.107* (1.64) (0.051)	-0.085* (-1.4) (0.077)

Note: Equation (2): $\text{SINE} = \begin{cases} 1 - \frac{\left(\sin\left(\pi \frac{julian}{182.5}\right)+1\right)}{2} & \text{in the Northern Hemisphere} \\ \frac{\left(\sin\left(\pi \frac{julian}{182.5}\right)+1\right)}{2} & \text{in the Southern Hemisphere} \end{cases}$

* Significant at the 10% level, one-sided test
** Significant at the 5% level, one-sided test
*** Significant at the 1% level, one-sided test

Table 5
Regression Results from Model
With SAD_t, D_t^{Fall}, D_t^{Tax} and Other Variables
$D_t^{Mon} = 1$ on first trading day following weekend
$D_t^{Tax} = 1$ on last and first five trading days of tax year
$SAD_t =$ value of Equation (2) during winter and fall; $D_t^{Fall} = 1$ during fall

$$r_t = \mu + \rho r_{t-1} + \mu_{Mon} D_t^{Mon} + \mu_{Tax} D_t^{Tax} + \mu_{SAD} SAD_t + \mu_{Fall} D_t^{Fall} + \epsilon_t$$

Country	$\hat{\mu}_{SAD}$ (t-test) (p-value)	$\hat{\mu}_{Fall}$ (t-test) (p-value)	$\hat{\mu}_{Tax}$ (t-test) (p-value)
United States EW	0.090***	-0.084***	0.313***
	(4.46)	(-4.8)	(6.91)
	(<0.001)	(<0.001)	(<0.001)
United States VW	0.077***	-0.045**	0.024
	(2.91)	(-2.0)	(0.40)
	(0.002)	(0.021)	(0.344)
Canada	0.108***	-0.072***	0.012
	(3.76)	(-2.9)	(0.19)
	(<0.001)	(0.002)	(0.424)
Britain	0.134***	-0.089***	0.097
	(2.87)	(-2.2)	(0.95)
	(0.002)	(0.015)	(0.171)
Germany	0.083**	-0.074**	0.128*
	(1.99)	(-2.1)	(1.41)
	(0.023)	(0.017)	(0.080)
Sweden	0.163***	-0.133***	0.183*
	(2.89)	(-2.8)	(1.49)
	(0.002)	(0.002)	(0.068)
Australia	0.015	0.021	0.142*
	(0.34)	(0.57)	(1.46)
	(0.367)	(0.284)	(0.073)
New Zealand	0.121**	-0.120**	0.257***
	(1.80)	(-1.7)	(2.53)
	(0.036)	(0.047)	(0.006)

Note: Equation (2): $$\text{SINE} = \begin{cases} 1 - \frac{\left(\sin\left(\pi \frac{julian}{182.5}\right)+1\right)}{2} & \text{in the Northern Hemisphere} \\ \frac{\left(\sin\left(\pi \frac{julian}{182.5}\right)+1\right)}{2} & \text{in the Southern Hemisphere} \end{cases}$$

Tax-year dummy variables were included for all countries. The variable equals one for the last trading day and the first five trading days of the tax year and equals zero otherwise. The tax year starts January 1 for all countries except Britain where the tax year starts April 6, Australia where the tax year starts July 1, and New Zealand where the tax year starts April 1.

* Significant at the 10% level, one-sided test
** Significant at the 5% level, one-sided test
*** Significant at the 1% level, one-sided test

Figure 1:
Hours of Night for Several Markets

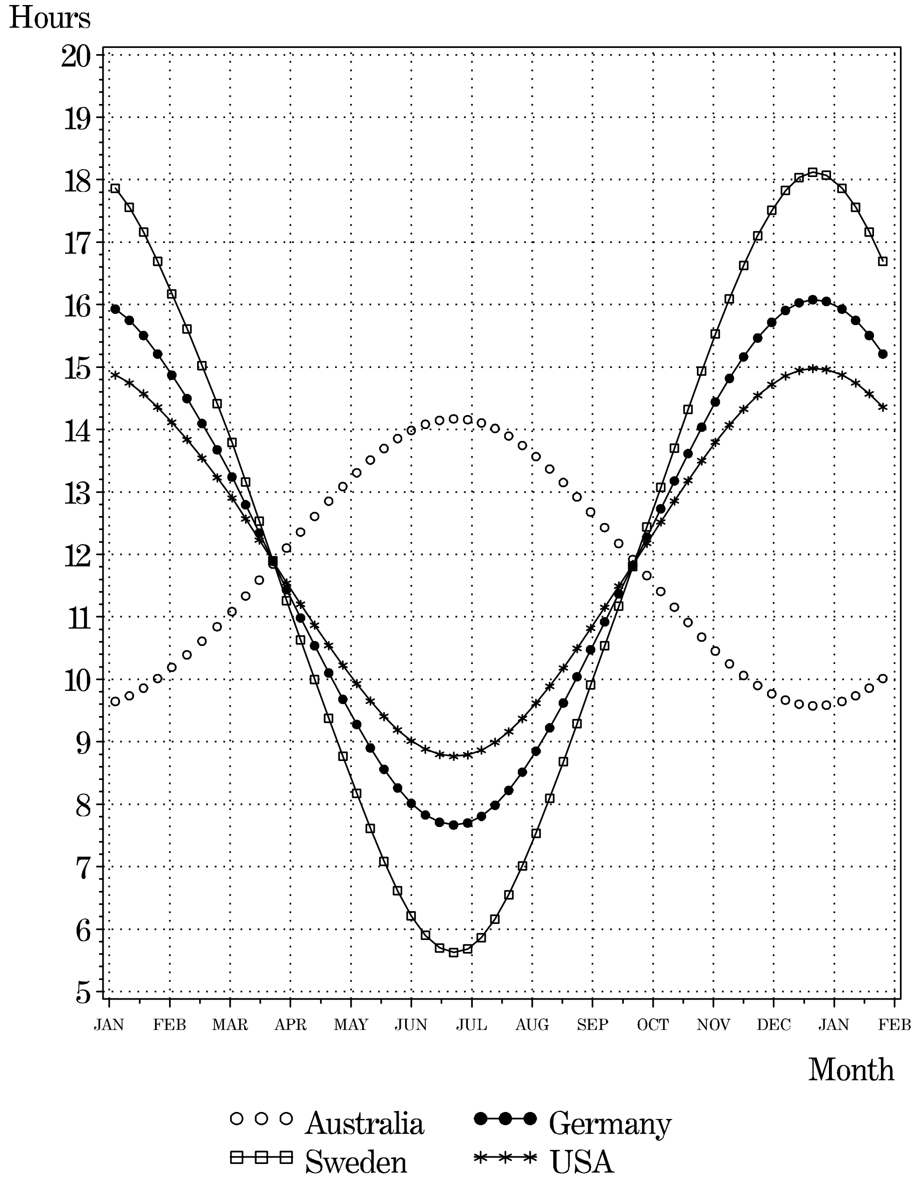

Figure 1: Actual hours of night are shown for the latitude at which each included country's stock exchange is located (rounded to the nearest degree). The latitudes, in degrees, are as follows: 34 South for Australia, 59 North for Sweden, 50 North for Germany, and 41 North for the United States.

Figure 2: Composite Plot of Value Weighted Data

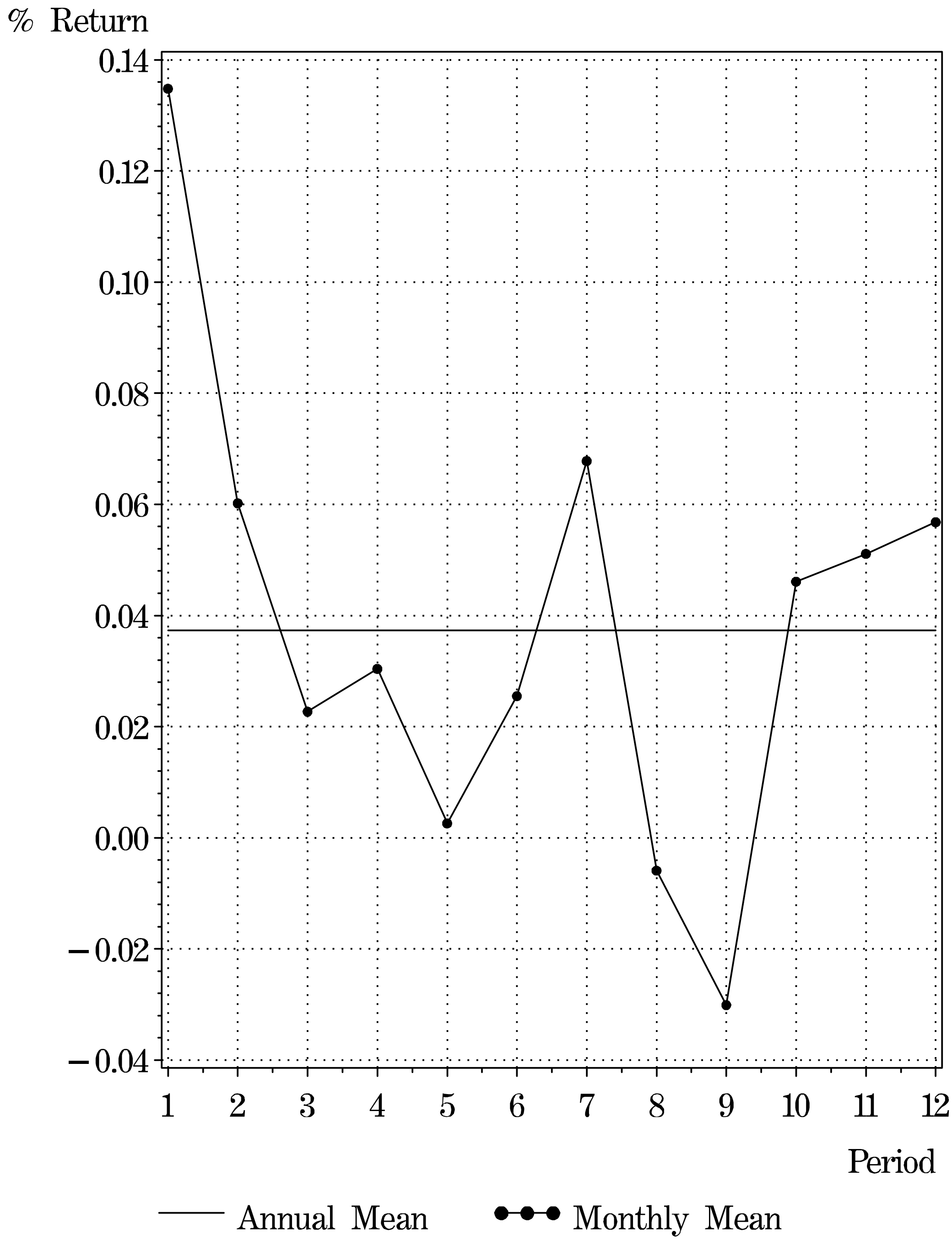

Figure 2: The Annual Mean represents the daily percentage returns averaged over the year across all seven value-weighted indices. The Monthly Mean represents the daily percentage returns averaged over each month across all seven value-weighted indices.

Figure 3: Individual Plots of Data for US, Canada, and Britain

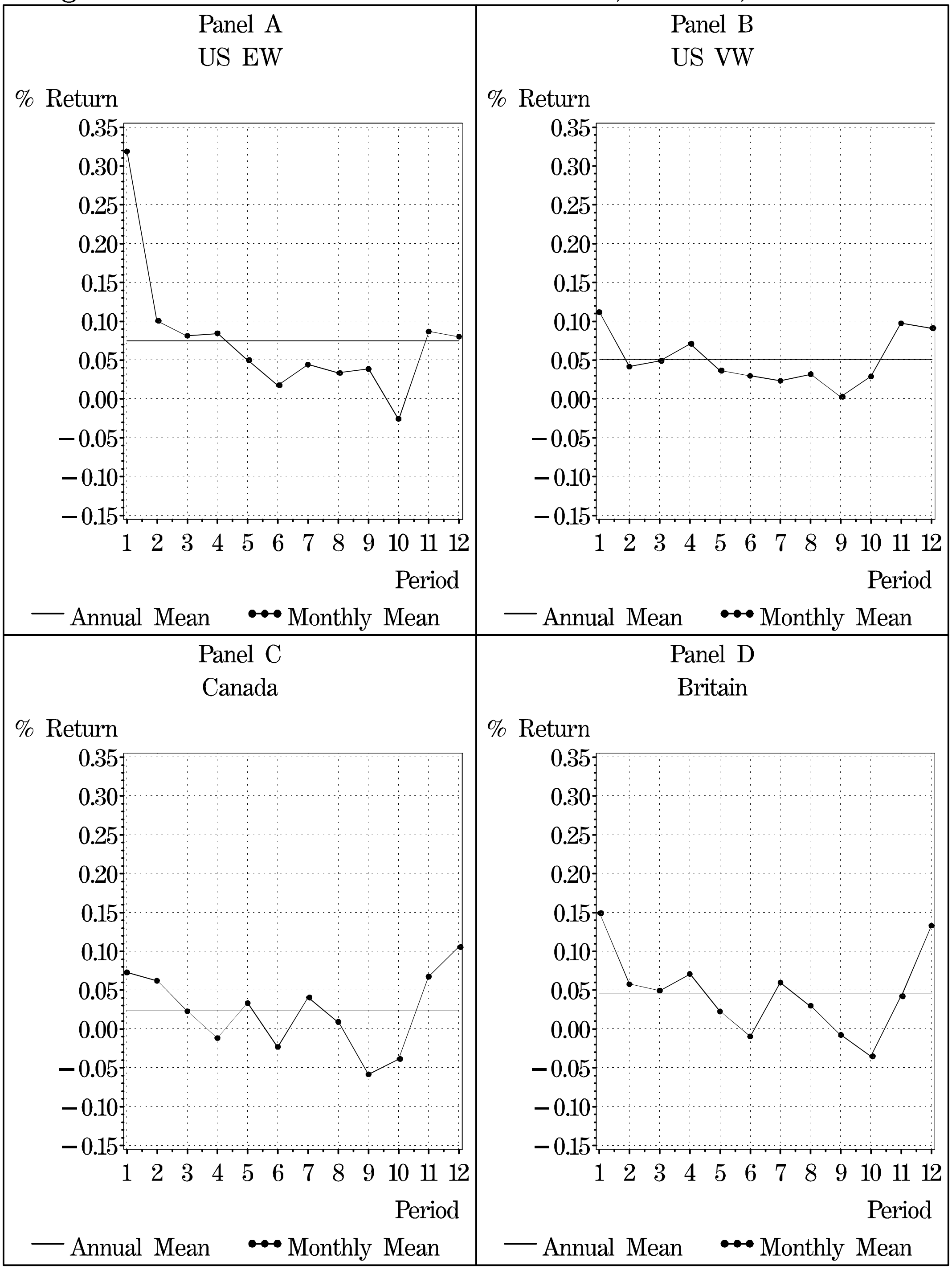

Figure 3: The Annual Mean for each index represents the daily percentage returns averaged over the year for that index. The Monthly Mean for each index represents the daily percentage returns averaged over each month for that index.

Figure 4: Individual Plots of Data for Germany, Sweden, Australia, and New Zealand

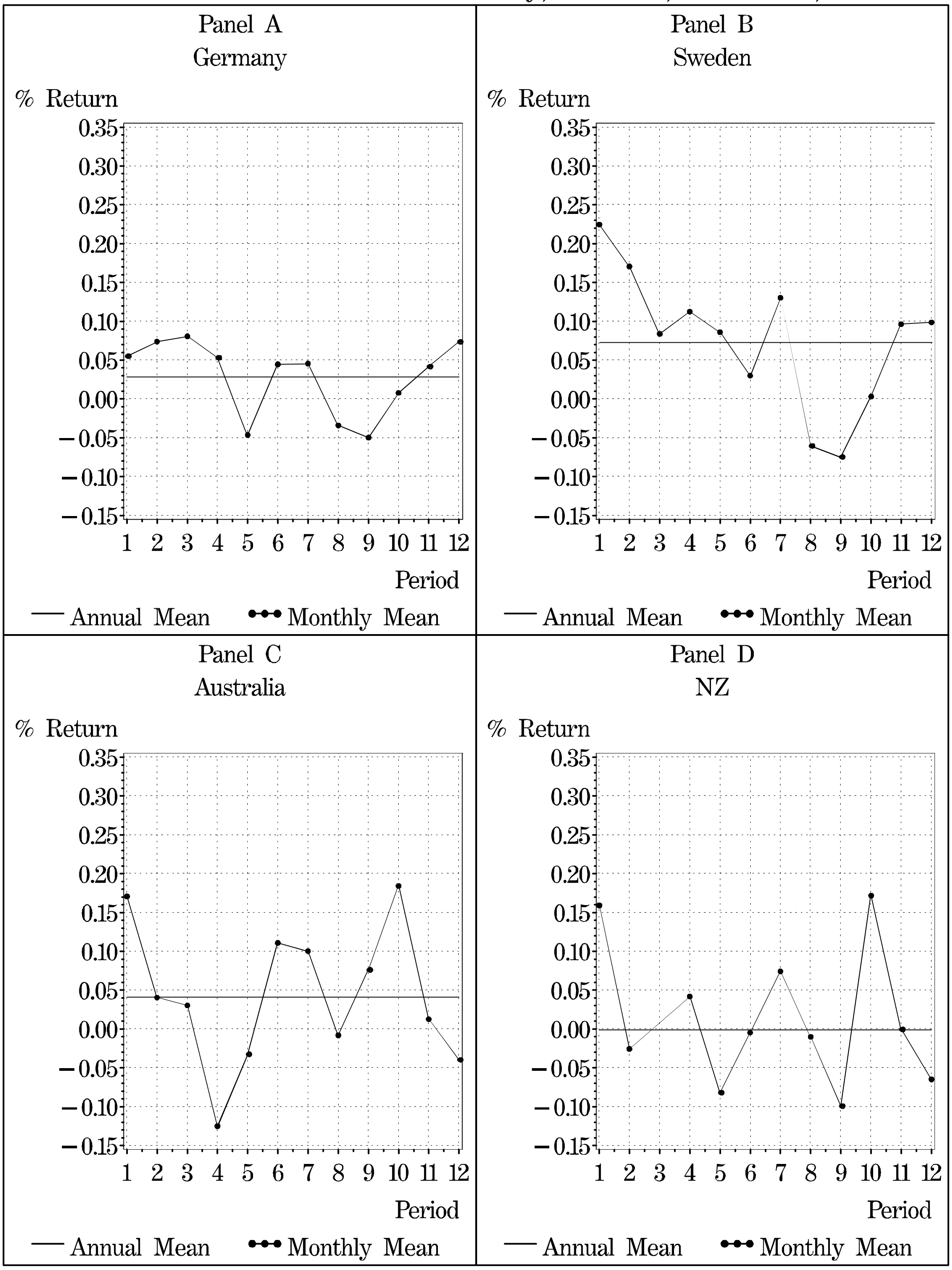

Figure 4: The Annual Mean for each index represents the daily percentage returns averaged over the year for that index. The Monthly Mean for each index represents the daily percentage returns averaged over each month for that index.

Figure 5:

Sine Wave for Each Hemisphere