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Journal of Empirical Finance 12 (2005) 291–316
Journal of EMPIRICAL FINANCE
www.elsevier.com/locate/econbase

Winter blues and time variation in the price of risk

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Accepted 27 January 2004
Available online 18 January 2005

Abstract

Previous research has documented robust links between seasonal variation in length of day, seasonal depression (known as seasonal affective disorder, or SAD), risk aversion, and stock market returns. The influence of SAD on market returns, known as the SAD effect, is large. We study the SAD effect in the context of an equilibrium asset pricing model to determine whether the seasonality can be explained using a conditional version of the CAPM that allows the price of risk to vary over time. Using daily and monthly data for the US, Sweden, New Zealand, the UK, Japan, and Australia, we find that a conditional CAPM that allows the price of risk to vary in relation to seasonal variation in the length of day fully captures the SAD effect. This is consistent with the notion that the SAD effect arises due to the heightened risk aversion that comes with seasonal depression, reflected by a changing risk premium.

JEL classification: G10; G12
Keywords: Stock market seasonality; Conditional CAPM; Time-varying risk aversion; Behavioral finance; Seasonal affective disorder

A recent development in finance has been the study of the effects of mood determinants on stock returns. Recent examples include the daylight saving effect (Kamstra et al.,

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doi:10.1016/j.jempfin.2004.01.002

2000), whereby returns following sleep disruptions on daylightsaving weekends are large and negative; the sunshine effect (Saunders, 1993; Hirshleifer and Shumway, 2003), where sunshine is significantly correlated with daily stock returns; and the seasonal affective disorder (SAD) effect (Kamstra et al., 2003) where seasonal variation in stock returns is linked to depression caused by reduced length of day in the fall and winter. An interesting question is whether such effects can be explained by a conditional asset pricing model which allows the risk premium to vary over time.

In this paper, we focus on one case in particular, the SAD effect. There are two good reasons for doing so. First, Kamstra, Kramer, and Levi (2003, henceforth KKL) document that the SAD effect is very robust.[1] Even after controlling for environmental effects such as sunshine, temperature and rainfall, and other well-known seasonals such as the tax-loss selling effect, there is still a very strong and significant SAD seasonal in stock returns whereby returns move in concert with length of day in both the Northern and Southern Hemispheres. This suggests the effect is worthy of further investigation. Second, experimental evidence from the psychology literature documents that depression such as that caused by SAD lowers the propensity for risk-taking.[2] Seasonal affective disorder and its less severe manifestation, the so-called winter blues, are clinical conditions in which sufferers experience depression during seasons of the year that have shorter daylight hours.[3] Given the link between depression and risk-taking, the SAD effect in stock returns may be captured by time variation in the risk premium in the context of an asset pricing model. This is the question we investigate in this paper.

Using both daily and monthly data, we confirm that there is a significant SAD effect in the stock markets we consider, including the US, Sweden, New Zealand, the UK, Japan, and Australia. If the SAD effect is related to time-varying risk premia, an asset pricing model that allows for time variation in the price of risk should be able to control for its presence. Following Bekaert and Harvey (1995), we investigate this possibility using a conditional version of the CAPM that allows the price of risk to vary over time. We find that allowing for a time-varying risk premium entirely accounts for the SAD effect in market returns.

The rest of the paper is organized as follows. The next section discusses seasonal affective disorder and how we measure its impact. Section 2 describes the data we use and documents the presence of the SAD effect in the markets we consider. In Section 3, we use a version of the conditional CAPM similar to that used by Bekaert and Harvey (1995) to show time variation in the risk premium is capable of explaining the SAD effect. Section 4 offers some concluding remarks.

[1] See the appendix to KKL which can be downloaded from http://www.markkamstra.com.

[2] The reliability of the measures used to measure the propensity for risk-taking in the context of financial decision making is well documented. See Harlow and Brown (1990), Wong and Carducci (1991), Horvath and Zuckerman (1993), and Tokunaga (1993), for example.

[3] SAD is clinically defined as a form of major depressive disorder, inducing long periods of prolonged sadness and profound, chronic fatigue. Evidence suggests that there is a *physiological* source to this depression. For more details, see Cohen et al. (1992), among others. Rosenthal (1998) notes that in the US, recurrent depression associated with shorter daylight hours is particularly severe for around 10 million people while some additional 15 million suffer from the milder winter blues.

1. Measurement of the SAD effect

Seasonal affective disorder is a condition linked to the amount of daylight through the course of the winter and fall. (See Molin et al. (1996) and Young et al. (1997) for further details.) To be clear, medical evidence shows that SAD is linked with daylight in the sense of *length of day*, which depends on season and latitude, not with amount of *sunshine*, which depends on cloudiness. Since the impact of seasonal affective disorder on sufferers becomes more pronounced as the number of hours of daylight decreases (equivalently, as the number of hours of night increases), our measure of SAD is based on the number of hours between sunset and sunrise in the fall and winter in a particular location, as in KKL.[4] To calculate our measure, we make use of results from spherical trigonometry. Define $julian_t$ as the number of the day in the year, taking on values ranging from t=1 to 365 (366 in a leap year).[5] Next calculate κ_t, the angle (in degrees) at which the sun declines each day at a particular location:

$$\kappa_t = 0.4102\sin\left[\left(\frac{2\pi}{365}\right)(julian_t - 80.25)\right]. \tag{1}$$

To compute the number of hours of night (H_t, the amount of time between sunrise and sunset) at a particular location, we need the location's latitude in degrees, denoted δ.[6] H_t is calculated as:

$$H_t = \begin{cases} 24 - 7.72\arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan(k_t)\right] & \text{in the Northern Hemisphere} \\ 7.72\arccos\left[-\tan\left(\frac{2\pi\delta}{360}\right)\tan(k_t)\right] & \text{in the Southern Hemisphere} \end{cases} \tag{2}$$

where 'arccos' is the arc cosine. We then deduct 12 from H_t to express the length of night relative to the annual average length of night. (Note that by working with hours of night, as opposed to day, the expected impact of the SAD measure on returns will be positive.)

$$\text{Daily length of night relative to annual average} = H_t - 12. \tag{3}$$

Since we are interested in measuring the impact of variation in length of night only during trading days in the fall and winter (the seasons for which medical practitioners have documented a systematic impact on mood due to SAD), we define our daily SAD measure only for trading days in the fall and winter:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

[4] For the northern hemisphere countries, we consider the start of the fall to be September 21, the start of the winter to be December 21, and the start of spring to be March 21, though the actual timing can vary from year-to-year by a couple of days. Corresponding dates for the southern hemisphere differ by 6 months.

[5] For example, $julian_t$ takes the value 1 on January 1, 2 on January 2 and so on.

[6] We use the latitude for the city in which a given country's stock exchange is located. Using instead the latitude of some other location within a given country would simply lead to an hours of night function with slightly different amplitude, leaving results reported in this paper qualitatively unchanged.

In Fig. 1, we plot the value of the daily SAD measure (i.e. Eq. (4)) for our Northern Hemisphere countries. The cycle with the most extreme values, indicated by the line with solid dots, corresponds to the SAD measure for Sweden. The peak of just over 6 for that

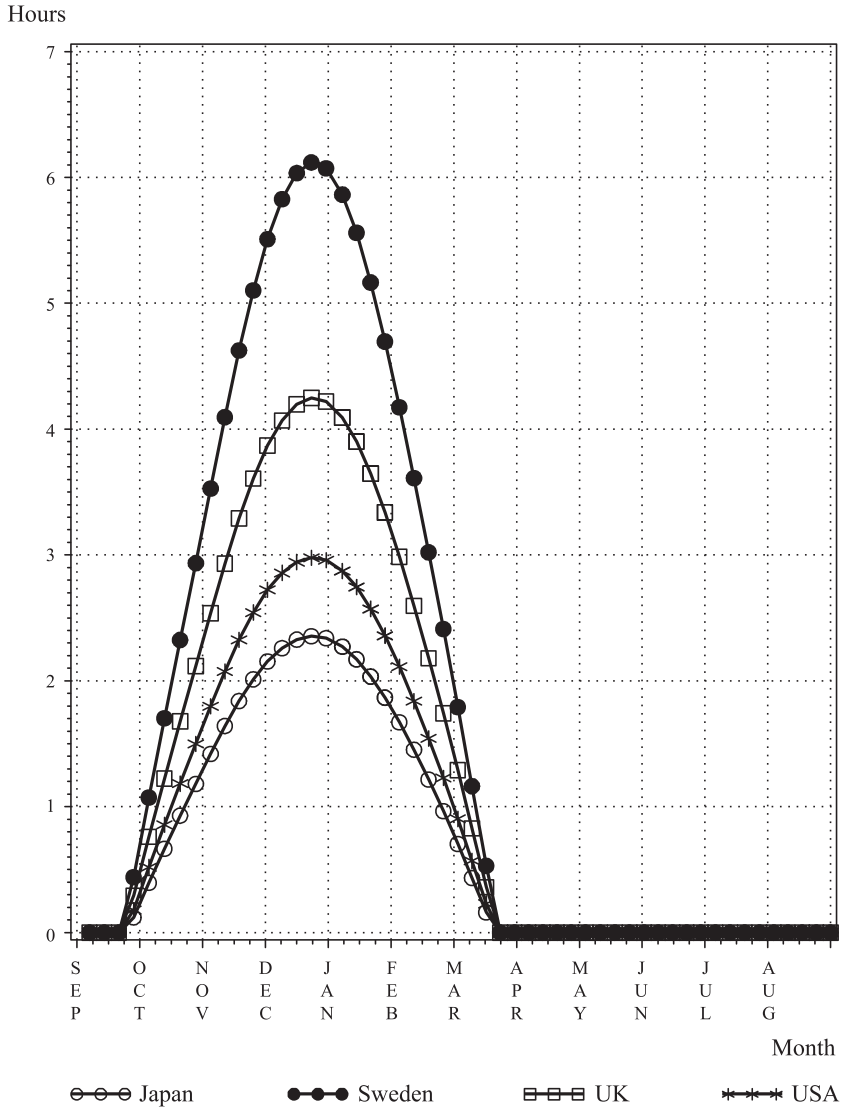

Fig. 1. SAD measure for Japan, Sweden, the UK, and the US. The daily SAD measure is shown for the UK, Japan, Sweden, and the US, based on the latitude of each country's largest stock exchange (rounded to the nearest degree): 59 North for Sweden, 51 North for the UK, 41 North for the United States, and 36 North for Japan. The daily SAD measure is defined as:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

cycle translates into a seasonal maximum of more than 18 h of night at the location of the Swedish stock exchange in Stockholm. The next most extreme cycle is for the UK, marked with hollow squares, followed by the US SAD measure, indicated by the line with asterisks. Finally, the least extreme values correspond to the cycle for Japan, marked with hollow dots. Of these four Northern Hemisphere countries, Japan is closest to the equator with the longest night of winter measuring about 14.5 h at the location of the stock exchange in Tokyo. Notice that for all the Northern Hemisphere countries, the SAD measure takes on non-zero values starting in late September and ending in late March, reflecting the medical evidence that individuals with SAD can experience symptoms as early as autumn equinox and as late as spring equinox. (See Dilsaver, 1990, for instance.) Fig. 2 reflects the SAD measure for New Zealand (hollow dots) and Australia (solid dots). Notice that the SAD measures shown in Fig. 2 take on non-zero values starting with the commencement of the Southern Hemisphere fall in late March and ending with the last day of winter in late September. Both Southern Hemisphere cycles peak in late June, consistent with winter solstice in the Southern Hemisphere.

A final point to consider in relation to measuring the effect of SAD is that stock returns may respond asymmetrically around winter solstice, the longest night of the year (December 21 in the Northern Hemisphere and June 21 in the Southern Hemisphere). As KKL (2003) suggest, the trading activities of investors affected by SAD may lead to different effects in the fall months versus the winter months. If investors become more risk averse during fall and return to normal by spring, then the returns to holding risky assets from the start of the fall to the end of the winter are generated by a starting price which is lower than would otherwise be observed. That is, with the increase in risk aversion experienced by SAD-affected investors in the fall, prices rise more slowly than they would otherwise. As the hours of daylight start to increase following winter solstice and SAD-afflicted individuals begin recovering, prices start to rebound from their initial lower level and returns rise. The implication is an asymmetry in returns: lower than average returns in the fall and above-average returns in the winter. To capture the effect of any asymmetry, we use the following interactive dummy variable:

$$Fall_t = \begin{cases} SAD_t & \text{for trading days in the fall} \\ 0 & \text{otherwise.} \end{cases} \quad (5)$$

If there is asymmetry around winter solstice, with lower returns in the fall relative to the winter, then the coefficient on the Fall variable will be negative.

In addition to the *SAD* and *Fall* variables described above which are defined on a daily frequency, we also require *monthly* versions of these variables. To this end, we convert the daily length of night variable into a monthly variable by using the median length of night for the month in question, defined as $\overline{H}_t$ for months t=1…12.[7] Then the monthly SAD measure is:

$$SAD_t = \begin{cases} \overline{H}_t - 12 & \text{for October} - \text{March} \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

[7] Use of the mean in place of the median leads to virtually identical results.

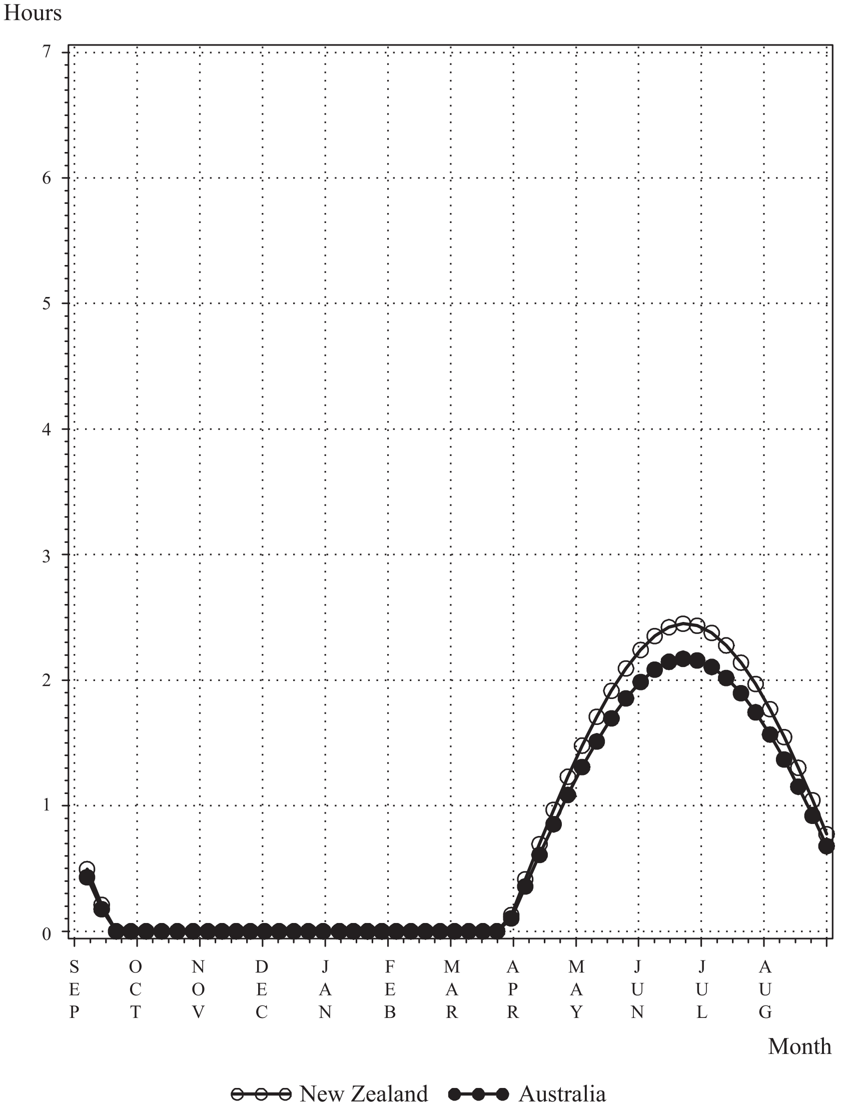

Fig. 2. SAD measure for New Zealand and Australia. The daily SAD measure is shown for New Zealand and Australia, based on the latitude of each country's largest stock exchange (rounded to the nearest degree): 37 South for New Zealand and 34 South for Australia. The daily SAD measure is defined as:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

The monthly counterpart to the daily Fall variable is based on the monthly SAD measure as follows:

$$Fall_t = \begin{cases} SAD_t & \text{for October} - \text{December} \\ 0 & \text{otherwise.} \end{cases} \quad (7)$$

2. Data and preliminary analysis of the SAD effect

Since our aim is to examine whether the SAD effect identified by KKL can be explained by time variation in the risk premium, our analysis starts by confirming the presence of the SAD effect in our data. The indices we consider are daily and monthly returns on the CRSP (NYSE, AMEX, and NASDAQ) value-weighted index including distributions for the US, the Veckans Affärer for Sweden, the Capital 40 for New Zealand, the FTSE 100 for the UK, the Nikkei 225 for Japan, and the All Ordinaries for Australia. The US series were obtained from CRSP while the other indices were obtained from Datastream. We consider monthly data in addition to daily data (KKL only consider daily) as the SAD effect should persist when returns are observed at a lower frequency and are less noisy. We also consider both raw returns and excess returns at both frequencies.

In computing *daily* excess returns, we subtract from the raw daily index returns for each country a corresponding daily risk-free rate based on the following: the 90-day T-Bill rate for the US (obtained from CRSP), the 90-day T-Bill rate for Sweden (obtained from Datastream), the 90-day Bank Bill yield for New Zealand (obtained from the Federal Reserve Bank of New Zealand web site), the 3-month T-bill rate for the UK, the 90-day Treasury Note rate for Australia, and the benchmark long bond yield for Japan (the last three were obtained from Datastream).[8] Note that all of the interest rates are quoted as annualized percentage rates. We calculate an approximate daily percentage rate as follows: $100 \times \left[1 + \left(\frac{r}{100}\right)^{\frac{1}{250}} - 1\right]$, where 250 is the approximate number of trading days in a calendar year. We calculate *monthly* excess returns by subtracting the one month Treasury Bill rate from the raw monthly index returns. The Treasury Bill rates used to calculate monthly excess returns for the US were obtained from the US Federal Reserve Board; for Sweden, New Zealand, the UK, and Japan, the rates were obtained from the IMF International Financial Statistics via Datastream; and for Australia, the rates were obtained from the Reserve Bank of Australia web site. Where required, rates quoted in annualized percentage form were converted to monthly rates in a manner similar to that described above.

In Table 1, we provide descriptive statistics for the raw and excess returns, both for daily and monthly frequencies. The top part of Panel A corresponds to daily raw returns and the bottom part of Panel A corresponds to daily returns in excess of the risk-free rate. The top part of Panel B reports statistics for the case of raw monthly returns, and the bottom portion pertains to monthly excess returns. At the top of each panel, we indicate

[8] We use the long bond yield for Japan because of the unavailability of daily short-term interest rate data for a sufficiently long period.

Table 1
Descriptive statistics for daily and monthly returns and daily and monthly excess returns

Panel A: Daily returns and daily excess returns

	US (41°N) 2/2/1962–29/12/2000	Sweden (59°N) 26/4/1989–29/12/2000	New Zealand (37°S) 1/7/1991–29/12/2000	UK (51°N) 3/1/1984–29/12/2000	Japan (36°N) 4/10/1982–29/12/2000	Australia (34°S) 7/7/1982–29/12/2000
Daily returns						
Mean (%)	0.0489	0.0501	0.0117	0.0421	0.0157	0.0416
Standard deviation (%)	0.8367	1.2367	0.9766	0.9842	1.3119	0.9894
Minimum	−18.100	−7.7385	−13.307	−13.029	−16.135	−28.761
Maximum	8.8700	9.7767	9.4750	7.5970	12.430	6.0666
Skewness	−1.1458	0.0219	−0.8515	−0.9958	−0.1914	−5.8717
Kurtosis	28.272	5.3727	19.961	13.947	10.174	158.62
AR	250.13***	44.463***	11.527	47.970***	51.714***	141.58
ARCH	1183.4***	533.42***	539.39***	2014.7***	550.50***	115.751***
Daily excess returns						
Mean (%)	0.0250	0.0200	−0.0161	0.0093	−0.0023	0.0053
Standard deviation (%)	0.8369	1.2372	0.9767	0.98472	1.3119	0.9892
Minimum	−18.127	−7.7836	−13.3386	−13.065	−16.159	−28.805
Maximum	8.8472	9.7601	9.4435	7.5602	12.400	6.0480
Skewness	−1.1519	0.0226	−0.8490	−0.9956	−0.1885	−5.8799
Kurtosis	28.248	5.3502	19.957	13.958	10.177	158.87
AR	250.90***	45.067***	11.551	48.007***	51.724***	140.93
ARCH	1183.3***	543.69***	537.07***	2015.0***	554.01***	116.97***

Panel B: Monthly returns and monthly excess returns

	US (41°N) 7/1926–12/2000	Sweden (59°N) 1/1975–12/2000	New Zealand (37°S) 7/1991–12/2000	UK (51°N) 2/1984–12/2000	Japan (36°N) 2/1960–12/2000	Australia (34°S) 8/1982–12/2000
Monthly returns						
Mean (%)	0.9943	1.3216	0.2470	0.9905	0.6904	0.8633
Standard deviation (%)	6.4281	5.9623	4.7100	4.7656	5.3664	5.7767
Minimum	−29.001	−23.931	−14.952	−26.044	−19.227	−55.244
Maximum	38.275	24.328	12.408	14.428	20.066	14.365
Skewness	0.1914	−0.3509	−0.1779	−0.9615	−0.2644	−4.1624
Kurtosis	7.9043	1.9471	0.3768	4.4832	1.1242	39.739
AR	35.404***	12.775	9.3191	10.872	7.5599	7.8908
ARCH	499.68***	16.764	22.639**	5.0830	55.445***	1.2601
Monthly excess returns						
Mean (%)	0.6815	0.5948	−0.3250	0.3123	0.1692	0.0232
Standard deviation (%)	5.5082	5.9611	4.7176	4.7629	5.3613	5.7597
Minimum	−29.031	−24.954	−15.567	−26.818	−19.787	−56.180
Maximum	38.175	23.202	11.914	13.437	19.448	13.024
Skewness	0.2286	−0.3673	−0.1500	−1.0079	−0.2543	−4.2462
Kurtosis	7.9308	1.9344	0.3943	4.5235	1.1205	40.496
AR	35.518***	12.905	9.0618	10.693	7.3892	7.9931
ARCH	503.66***	15.318	23.153**	5.2684	62.456***	0.9315

Panel A reports descriptive statistics for daily returns on the US CRSP (NYSE, AMEX, and NASDAQ) value-weighted index including distributions, the Swedish Veckans Affärer index, the New Zealand Capital 40 index, the FTSE 100 UK index, the Nikkei 225 Japanese index, and the All Ordinaries Australian index, as well as daily excess returns for the same indices. Panel B reports descriptive statistics for monthly returns on the same indices. AR and ARCH are Ljung–Box statistics testing for up to 10th-order serial correlation and ARCH in daily returns and excess returns and up to 12th-order serial correlation and ARCH in monthly returns and excess returns. These tests are distributed $\chi^2(10)$ for daily returns and $\chi^2(12)$ for monthly returns under the respective null hypotheses of no serial correlation and no ARCH. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 2
The SAD effect in daily returns

	US (41°N) 2/2/1962–29/12/2000	Sweden (59°N) 26/4/1989–29/12/2000	New Zealand (37°S) 1/7/1991–29/12/2000	UK (51°N) 3/1/1984 –29/12/2000	Japan (36°N) 4/10/1982–29/12/2000	Australia (34°S) 7/7/1982–29/12/2000
Panel A: Returns						
μ_0	0.0522*** (4.795)	−0.0048 (−0.168)	0.0387* (1.381)	0.03573* (1.8228)	0.0203 (0.790)	0.0357 (1.576)
μ_{SAD}	0.0256*** (2.554)	0.0527*** (3.725)	0.0327* (1.468)	0.0330*** (2.716)	0.0480* (1.531)	0.0268* (1.503)
μ_{Fall}	−0.0183* (−1.463)	−0.0468*** (−2.652)	−0.0467** (−1.825)	−0.0247** (−1.673)	−0.0467* (−1.276)	−0.00313* (−1.575)
ρ_1	0.1635*** (6.749)	0.0975*** (3.237)	0.0347 (0.496)	0.0732 (1.520)	0.0074 (0.261)	0.1128** (2.427)
ρ_2	−0.0415* (−1.601)	–	–	–	−0.0831*** (−3.901)	−0.0592* (−1.934)
μ_{Mon}	−0.1250*** (−5.164)	0.0079 (0.128)	−0.1897*** (−3.394)	−0.1246*** (−3.039)	−0.0829 (−1.520)	−0.0490 (−1.325)
μ_{Tax}	0.0504 (0.718)	0.0288 (0.147)	0.1490 (0.861)	0.0651 (0.759)	−0.1397 (−0.893)	0.1764** (2.132)
AR	7.1696	14.587	7.8650	16.361	18.79	7.8650
ARCH	963.08***	295.77***	657.94***	1653.2***	626.47***	139.61***
Panel B: Excess returns						
μ_0	0.0312*** (2.891)	−0.0319 (−1.129)	0.0122 (0.443)	0.0055* (0.283)	0.0009 (0.035)	0.0009 (0.043)
μ_{SAD}	0.0255*** (2.553)	0.0528*** (3.727)	0.0322* (1.445)	0.0328*** (2.698)	0.0480* (1.531)	0.0271* (1.523)
μ_{Fall}	−0.0184* (−1.466)	−0.0468*** (−2.655)	−0.0465** (−1.818)	−0.0245** (−1.656)	−0.0467* (−1.277)	−0.0311* (−1.568)
ρ_1	0.1640*** (6.765)	0.0985*** (3.271)	0.0350 (0.500)	0.0732 (1.522)	0.0073 (0.259)	0.1126** (2.422)
ρ_2	−0.0410* (−1.582)	–	–	–	−0.0832*** (−3.902)	−0.0594* (−1.943)
μ_{Mon}	−0.1249*** (−5.158)	0.0079 (0.128)	−0.1898*** (−3.395)	−0.1247*** (−3.039)	−0.0828 (−1.518)	−0.0489 (−1.324)
μ_{Tax}	0.0502 (0.716)	0.0281 (0.143)	0.1477 (0.853)	0.0652 (0.758)	−0.1400 (−0.895)	0.1772** (2.141)
AR	6.8617	14.435	7.8441	16.405	18.752	7.8411
ARCH	964.75***	296.79***	658.63***	1653.2***	627.74***	139.67***

the name of each country, the latitude of the corresponding exchange (rounded to the nearest degree), and the time period we study. Note that the time periods differ across exchanges based on data availability, and for a number of exchanges we are able to extend the time period by using monthly data. We provide the mean, standard deviation, minimum, maximum, skewness, and kurtosis for each index, as well as Ljung–Box χ^2 statistics for testing for the presence of autocorrelation (denoted AR) or ARCH up to 10 (daily) or 12 (monthly) lags. We find returns display typical properties, including, in some cases, evidence suggestive of non-normality, autocorrelation and ARCH. The indices for the US and Australia are notable in that they contain the largest negative outliers at both the daily and monthly frequencies.

We now turn to an analysis of the SAD effect in both the daily and monthly data. We perform a preliminary formal test for the SAD effect in each country, allowing for asymmetry around winter solstice. Similar to KKL, the model we estimate for daily returns is

$$R_{it} = \mu_0 + \mu_{SAD}SAD_t + \mu_{Fall}Fall_t + \sum_{j=1}^{p} \rho_j R_{it-j} + \mu_{Mon}Mon_t + \mu_{Tax}Tax_t + \varepsilon_{it} \qquad (8)$$

where R_{it} are daily returns for country i on day t; SAD_t is defined by Eqs. (1–4) using latitudes of New York City (41°N), Stockholm (59°N), Auckland (37°S), London (51°N), Tokyo (36°N), and Sydney (34°S); $Fall_t$ is a variable that takes the value of SAD_t from September 21 through December 20 for the Northern Hemisphere countries, the value of SAD_t from March 21 to June 20 for Australia and New Zealand, and zero otherwise; Mon_t

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Notes to Table 2:
Panel A reports parameter estimates from the regression

$$R_{it} = \mu_0 + \mu_{SAD}SAD_t + \mu_{Fall}Fall_t + \sum_{j=1}^{p} \rho_j R_{it-j} + \mu_{Mon}Mon_t + \mu_{Tax}Tax_t + \varepsilon_{it} \qquad (8)$$

where R_{it} are daily returns for country i on day t; SAD_t is a measure based on the normalized number of hours of night in fall and winter; $Fall_t$ is an interactive dummy variable that takes the value of SAD_t from September 21 through December 20 for the US, Sweden, the UK, and Japan, the value of SAD_t from March 21 to June 20 for New Zealand and Australia, and 0 otherwise; Mon_t is a dummy variable that takes the value 1 on Mondays (or the first trading day following a long weekend) and 0 otherwise; and Tax_t is a dummy variable that takes the value 1 for the day prior to and the 4 days following the start of a tax year and 0 otherwise.
Panel B reports parameter estimates from the regression

$$r_{it} = \mu_0 + \mu_{SAD}SAD_t + \mu_{Fall}Fall_t + \sum_{j=1}^{p} \rho_j r_{it-j} + \mu_{Mon}Mon_t + \mu_{Tax}Tax_t + \varepsilon_{it} \qquad (9)$$

where r_{it} are daily excess returns for country i. Regressions in both Panels A and B include at least one lag of the dependent variable (p=1) to control for residual autocorrelation; the US, Japan, and Australia require two lags (p=2). The null hypotheses with respect to the SAD effect are H_0: μ_{SAD}=0 and H_0: μ_{Fall}=0 against the alternatives H_A: μ_{SAD}>0 and H_A: μ_{Fall}<0, respectively. Figures in parentheses are White (1980) heteroskedasticity-consistent t-statistics. AR and ARCH are Lagrange multiplier tests for up to 10th-order serial correlation and ARCH in ε_{it}. Both are distributed $\chi^2(10)$ under the respective null hypotheses of no serial correlation and no ARCH. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

Table 3
The SAD effect in monthly returns

	US (41°N) 7/1926–12/2000	Sweden (59°N) 1/1975–12/2000	New Zealand (37°S) 7/1991–12/2000	UK (51°N) 2/1984–12/2000	Japan (36°N) 2/1960–12/2000	Australia (34°S) 8/1982–12/2000
Panel A: Returns						
μ_0	0.7888*** (2.688)	0.2568 (0.649)	0.0717 (0.1310)	0.5513 (1.331)	0.1957 (0.615)	0.5452 (0.994)
μ_{SAD}	0.2720* (1.240)	0.7053*** (3.274)	0.7358* (1.395)	0.4700* (1.452)	1.1970*** (3.510)	1.0713*** (1.976)
μ_{Fall}	−0.0256 (−0.112)	−0.3994* (−1.581)	−0.8694* (−1.329)	−0.1447 (−0.423)	−0.8382*** (−2.103)	−1.0613*** (−2.073)
ρ_1	0.0988** (1.667)	0.1577*** (2.352)	−0.1457* (−1.299)	−0.0250 (−0.260)	−0.0004 (−0.006)	−0.0441 (−0.965)
ρ_2	−0.0108 (−0.1999)	–	–	–	–	–
ρ_3	−0.1150** (−1.992)	–	–	–	–	–
AR	14.881	1.1728	6.1260	10.978	8.2298	7.5064
ARCH	188.64***	10.144	15.086*	5.7975	43.054***	0.6535
Panel B: Excess returns						
μ_0	0.4574* (1.635)	−0.3572 (−0.936)	−0.5738 (−1.046)	−0.1426 (−0.352)	−0.3265 (−1.047)	−0.3277 (−0.575)
μ_{SAD}	0.2761* (1.254)	0.7066*** (3.283)	0.7244* (1.366)	0.4667* (1.458)	1.1984*** (3.516)	1.0725*** (2.017)
μ_{Fall}	−0.0269 (−0.118)	−0.3996* (−1.584)	−0.8635* (−1.315)	−0.1410 (−0.416)	−0.8374*** (−0.564)	−1.0674*** (−2.123)
ρ_1	0.1028** (1.723)	0.1575*** (2.340)	−0.1408 (−1.259)	−0.0243 (−0.252)	−0.0021 (−0.036)	−0.0464 (−1.023)
ρ_2	−0.008 (−0.151)	–	–	–	–	–
ρ_3	0.1125** (−1.961)	–	–	–	–	–

AR	15.059	1.3111	6.0640	10.596	8.1101	7.4793
ARCH	188.56***	14.996	20.058*	5.9042	43.429***	0.6086

Panel A reports parameter estimates from the regression

$$R_{it} = \mu_0 + \mu_{SAD} SAD_t + \mu_{Fall} Fall_t + \sum_{j=1}^{p} \rho_j R_{it-j} + \varepsilon_{it} \tag{10}$$

where R_{it} are monthly returns for country i in month t; SAD_t is a measure based on the normalized median monthly number of hours of night in fall and winter; $Fall_t$ is a variable that takes the value of SAD_t during October through December for the US, Sweden, the UK, and Japan, the value of SAD_t during April through June for New Zealand and Australia, and 0 otherwise.

Panel B reports parameter estimates from the regression

$$r_{it} = \mu_0 + \mu_{SAD} SAD_t + \mu_{Fall} Fall_t + \sum_{j=1}^{p} \rho_j r_{it-j} + \varepsilon_{it} \tag{11}$$

where r_{it} are monthly excess returns for country i. Regressions in both Panels A and B include at least one lag of the dependent variable (p=1) to control for residual autocorrelation; the US requires three lags (p=3). The null hypotheses with respect to the SAD effect are H_0: $\mu_{SAD}=0$ and H_0: $\mu_{Fall}=0$ against the alternatives H_A: $\mu_{SAD}>0$ and H_A: $\mu_{Fall}<0$, respectively. Figures in parentheses are White (1980) heteroskedasticity-consistent t-statistics. AR and ARCH are Lagrange multiplier tests for up to 12th-order serial orrelation and ARCH in ε_{it}. Both are distributed $\chi^2(12)$ under the respective null hypotheses of no serial correlation and no ARCH. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

is a dummy variable that takes the value 1 on Mondays (or the first trading day following a long weekend) and 0 otherwise; and Tax_t is a tax-loss selling dummy variable that takes the value 1 for the day prior to and the 4 days following the start of a tax year and 0 otherwise.[9,10,11] Up to p lags of the dependent variable, $\sum_{j=1}^{p} R_{it-j}$, are included to control for autocorrelation in ε_{it}. We also estimate the model using daily excess returns:

$$r_{it} = \mu_0 + \mu_{SAD} SAD_t + \mu_{Fall} Fall_t + \sum_{j=1}^{p} \rho_j r_{it-j} + \mu_{Mon} Mon_t + \mu_{Tax} Tax_t + \varepsilon_{it}, \quad (9)$$

where r_{it} are daily excess returns for country i. Using monthly returns for country i, we estimate[12]

$$R_{it} = \mu_0 + \mu_{SAD} SAD_t + \mu_{Fall} Fall_t + \sum_{j=1}^{p} \rho_j R_{it-j} + \varepsilon_{it}, \quad (10)$$

and using monthly excess returns for country i, we estimate

$$R_{it} = \mu_0 + \mu_{SAD} SAD_t + \mu_{Fall} Fall_t + \sum_{j=1}^{p} \rho_j R_{it-j} + \varepsilon_{it}. \quad (11)$$

The null hypotheses of interest in all cases are H_0: μ_{SAD}=0 and H_0: μ_{Fall}=0 against the one-sided alternatives H_A: μ_{SAD}>0 and H_A: μ_{Fall}<0, respectively.

Estimation results from these regressions are provided in Panel A (raw returns) and Panel B (excess returns) of Tables 2 and 3. Throughout the tables in the remainder of this paper, robust standard errors appear in parentheses beneath parameter estimates. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. Notice that for the most part we reject the null hypotheses above: the SAD variable is significantly positive and the Fall variable is significantly negative. (In the few cases where the SAD or Fall variable is insignificant, the expected sign is still observed.) That is, returns increase during the SAD months, consistent with the notion that investors who suffer from SAD require higher returns to be induced to hold equity. The negative coefficient on the Fall variable indicates that returns respond asymmetrically around winter solstice, suggesting SAD-affected investors sell risky assets as they become more risk averse in the fall and then begin to resume risky holdings as daylight becomes more plentiful. Overall, the results in Tables 2 and 3 confirm and reinforce those of KKL.

[9] KKL define $Fall_t$ as a dummy variable equal to 1 in the fall and 0 otherwise. Their specification is a relatively more crude measure of asymmetry, but we find similar results using either measure.

[10] Keim (1983), Ritter (1988), and others have found that the effects of tax-loss selling are concentrated in the trading day before and the few trading days following a change of tax year.

[11] KKL also include cloud cover, temperature and precipitation in their version of Eq. (8) but find, with rare exception, that none of these variables are significant in the nine countries they study.

[12] We do not control for tax-loss selling effects in the monthly return regressions because of its insignificance in almost all the daily regressions. (See Table 2.) As a robustness check, we ran monthly regressions including a monthly Tax_t variable and found parameter estimates were qualitatively identical to those reported for the daily regressions.

3. SAD and time variation in market risk and the market price of risk

The results in the previous section document the presence of a SAD effect, captured by SAD_t and $Fall_t$, in both daily and monthly stock returns. Given that SAD is a depressive disorder and given that depression lowers the propensity to take risk, a natural question that follows is whether the SAD effect can be captured by allowing time variation in the risk premium. In order to examine this possibility, we consider a conditional version of Merton's (1980) CAPM. See also Bekaert and Harvey (1995) and Malliaropulos and Priestley (1999).

For an individual asset k, the conditional CAPM is (see Harvey, 1989; Bekaert and Harvey, 1995)

$$E_{t-1}(r_{kt}) = \lambda cov_{t-1}(r_{kt}r_{mt}) \tag{12}$$

where r_{kt} are excess returns on the asset, r_{mt} are excess returns on the market portfolio, λ is the price of covariance risk, and cov is the time-varying conditional covariance between excess returns on the asset and on the market portfolio. For the expected excess return on the market, Eq. (12) becomes

$$E_{t-1}(r_{mt}) = \lambda var_{t-1}(r_{mt}) \tag{13}$$

where var is the time-varying conditional variance of the market. The empirical counterpart of Eq. (13) we use is

$$r_{mt} = \lambda var_{t-1}(r_{mt}) + \xi_{mt} \tag{14}$$

where ξ_{mt} is an error term.

To operationalize Eq. (14), we need a model for $var_{t-1}(r_{mt})$. An obvious approach, and one that is popular in the literature, is to view Eq. (14) as a GARCH in Mean (GARCH-M) model and allow the variance of ξ_{mt} to evolve according to a GARCH process (see, for example, Malliaropulos and Priestley, 1999; Bekaert and Harvey, 1995; Glosten et al., 1993; Nelson, 1991). We allow the conditional variance of ξ_{mt} to evolve according to the Exponential GARCH (EGARCH) specification of Nelson (1991). This model allows the conditional variance to respond asymmetrically to positive and negative shocks[13] and has the additional benefit that, unlike the GARCH model and the Glosten et al. (1993) asymmetric GARCH model, no non-negativity constraints are required on the parameters of the EGARCH process to ensure that the conditional variance is positive. Supplementing Eq. (14) with the EGARCH specification of the conditional variance yields

$$r_{mt} = \lambda var_{t-1}(r_{mt}) + \xi_{mt} \tag{15}$$

$$var_{t-1}(r_{mt}) = h_t = \exp\left\{\omega + \beta \ln(h_{t-1}) + \alpha\left(\frac{|\xi_{mt-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \theta\left(\frac{\xi_{mt-1}}{\sqrt{h_{t-1}}}\right)\right\}$$

where h_t is market risk and λ is the price of this market risk. Asymmetry in the conditional variance is captured by $\theta\left(\frac{\xi_{t-1}}{\sqrt{h_{t-1}}}\right)$. If θ is negative, and there is a wealth of empirical evidence demonstrating that it typically is, negative ξ will increase volatility while positive

[13] This allows for the so-called leverage effect: If ξ_{mt} is negative, the market value of equity falls which leads to an increase in leverage. In turn, equity becomes more risky, hence the conditional variance will increase.

ξ will decrease volatility. An interesting first question to ask is whether allowing market risk alone to vary is sufficient to explain the *SAD* effect. In other words, natural hypotheses that follow from Eq. (15) are whether there is any remaining predictability relating to SAD_t and $Fall_t$ once time variation in market risk is accounted for. This corresponds to testing H_0: μ^*_{SAD}=0 and H_0: μ^*_{Fall}=0 in

$$\hat{\xi}_{mt} = \mu^*_0 + \mu^*_{SAD}SAD_t + \mu^*_{Fall}Fall_t + e_{mt}. \tag{16}$$

It is also interesting to consider the role of λ in Eq. (13)—and hence Eq. (14)—in the context of the SAD effect. Merton (1980) argues that λ is the weighted sum of the reciprocal of each investor's coefficient of relative risk aversion, with the weight being related to the distribution of wealth among individuals. Given that the marginal trader sets prices, and given the evidence that SAD increases risk aversion, it is possible that if the marginal investor suffers from SAD and this investor's coefficient of relative risk aversion receives a reasonably large weight in λ because of the distribution of wealth, SAD will affect λ directly. In other words, the price of risk, λ, will be a parametric function of the SAD and Fall variables. Allowing λ to vary with time, and defining λ_0 as the value λ takes when both SAD_t and $Fall_t$ equal zero, we set λ_t=λ_0+$\lambda_{SAD}SAD_t$+$\lambda_{Fall}Fall_t$.[14] Then Eq. (15) becomes

$$r_{mt} = (\lambda_0 + \lambda_{SAD}SAD_t + \lambda_{Fall}Fall_t)var_{t-1}(r_{mt}) + \eta_{mt} \tag{17}$$

$$var_{t-1}(r_{mt}) = h_t = \exp\left\{\omega + \beta\ln(h_{t-1}) + \alpha\left(\frac{|\eta_{mt-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \theta\left(\frac{\eta_{mt-1}}{\sqrt{h_{t-1}}}\right)\right\}$$

There are several hypotheses of interest that follow from Eq. (17). First, if SAD_t and $Fall_t$ do influence the price of risk, and hence the coefficient of relative risk aversion, we would expect λ_{SAD} to be positive and λ_{Fall} to be negative. Second, if the SAD effect can be explained by Eq. (17), there should be no remaining predictability in η_{mt}, which measures returns adjusted for systematic risk, due to SAD_t and $Fall_t$. This corresponds to testing H_0: μ^*_{SAD}=0 and H_0: μ^*_{Fall}=0 against the appropriate one-sided alternatives in

$$\hat{\eta}_{mt} = \mu^*_0 + \mu^*_{SAD}SAD_t + \mu^*_{Fall}Fall_t + \mu_{mt} \tag{18}$$

We test these hypotheses in the following sections.

3.1. Results using daily excess returns

The results from estimating Eq. (15) using daily excess returns are reported in Table 4.[15] Several observations are in order here. The first point to note is that the models

[14] Bekaert and Harvey (1995) and Malliaropulos and Priestley (1999) constrain the price of risk to be positive, which it should be if λ_t is to be interpreted as the coefficient of relative risk aversion. We choose not to constrain λ_t to be positive because the sign of the relationship between return and risk is far from clear empirically. For example, French et al. (1987) find an insignificant relationship between return and volatility, Harvey (1989) finds a significant positive relationship, while Glosten et al. (1993) find a significant negative relationship.

[15] Consistent with the estimation of Eq. (8), results for which are shown in Table 2, we also control for Monday and tax effects and autocorrelation in returns in the estimation of Eq. (15), as shown at the top of Table 4.

Table 4

Daily time variation in market risk (λ, the price of risk, held constant)

	US (41°N) 2/2/1962–29/12/2000	Sweden (59°N) 26/4/1989–29/12/2000	New Zealand (37°S) 1/7/1991–29/12/2000	UK (51°N) 3/1/1984–29/12/2000	Japan (36°N) 4/10/1982–29/12/2000	Australia (34°S) 7/7/1982–29/12/2000
μ_0	0.0246*** (5.935)	0.0051 (0.151)	−0.0161* (−1.638)	0.0229*** (2.204)	0.0493* (1.864)	−0.0034 (−0.374)
λ_0	0.0280*** (3.494)	−0.0008 (−0.051)	0.0498** (2.273)	0.0095 (0.709)	−0.0211 (−1.343)	0.0067 (0.473)
ρ_1	0.1995*** (20.94)	0.1420*** (8.665)	0.1205*** (5.035)	0.0779*** (5.008)	0.0341* (1.865)	0.1628*** (11.14)
Mon_t	−0.1096*** (−9.013)	0.0290 (1.1097)	−0.1753*** (−6.535)	−0.1438*** (−5.211)	−0.0471 (−1.453)	−0.0290* (−1.751)
Tax_t	0.0461 (1.315)	0.3598*** (3.272)	−0.0315 (−0.303)	0.0396 (0.417)	−0.1678 (−1.639)	0.1931** (2.563)
ω	−0.0068*** (−10.79)	0.0177*** (2.541)	−0.0149*** (−4.434)	−0.0041*** (−3.464)	0.0284*** (8.271)	−0.0377*** (−11.43)
β	0.9835*** (640.00)	0.9515*** (82.152)	0.9052*** (48.15)	0.9681*** (352.4)	0.9581*** (200.5)	0.8446*** (144.8)
α	0.1423*** (36.66)	0.1905*** (4.874)	0.3114*** (6.611)	0.1683*** (17.63)	0.2663*** (27.38)	0.3508*** (30.12)
θ	−0.0840*** (−28.66)	−0.0814*** (−5.344)	−0.0558** (−1.937)	−0.0534*** (−12.34)	−0.1410*** (−19.93)	−0.1188** (−14.61)
AR	10.584	14.476	4.6783	10.298	12.709	17.750
ARCH	10.461	2.0146	14.895	15.394	4.3018	5.7712

The table reports parameter estimates from

$$r_{it} = \mu_0 + \lambda_0 h_{it} + \rho_1 r_{it-1} + \mu_{Mon} Mon_t + \mu_{Tax} Tax_t + \xi_{it} \qquad (15')$$

$$h_{it} = \exp\left\{ \omega + \beta \ln(h_{it-1}) + \alpha\left(\frac{|\xi_{it-1}|}{\sqrt{h_{it-1}}} - \sqrt{\frac{2}{\pi}}\right) + \theta\left(\frac{|\xi_{it-1}|}{\sqrt{h_{it-1}}}\right)\right\}$$

where r_{it} are daily excess returns, Mon_t is a dummy variable that takes the value 1 on Mondays (or the first trading day following a long weekend) and 0 otherwise; and Tax_t is a dummy variable that takes the value 1 for the day prior to and the 4 days following the start of a tax year and 0 otherwise. One lag of the dependent variable is included to control for residual autocorrelation. (This is Eq. (15) adjusted to control for autocorrelation and Monday and tax effects in returns.) The model is estimated using Quasi Maximum Likelihood methods (Bollerslev and Wooldridge, 1992) to provide t-statistics that are robust to departures from conditional normality. These robust t-statistics are reported in parentheses below the relevant parameter estimates. AR and ARCH are Lagrange multiplier tests for up to 10th-order serial correlation and ARCH in ξ_{it}. Both are distributed $\chi^2(10)$ under the respective null hypotheses of no serial correlation and no ARCH. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

seem to be well-specified: there is no evidence of serial correlation, and the EGARCH specification seems to do a good job of capturing the ARCH effects present in the data. The asymmetry permitted by the EGARCH model evidently matters, as θ is consistently significant and negative. This means asymmetry is important in the specification of the model for the conditional variance, and negative shocks to returns increase volatility relative to positive shocks. All of the other GARCH terms are similarly very significant. In no country is λ_0 significantly negative, implying variance (market risk) may be positively related to returns in at least some of the countries we consider.

An interesting question at this stage is whether Eq. (15) is sufficient to explain the SAD effect identified in excess returns in Section 2. If so, the residuals from Eq. (15) should not contain evidence of the SAD effect. Results from estimating Eq. (16) (testing for the SAD effect in the residuals from Eq. (15)) are presented in Table 5. The SAD coefficient estimate is everywhere positive, significantly so in four of the six countries The Fall coefficient estimate is negative for all countries considered, significant in every case but one. The results in Table 5 clearly show that simply allowing market risk to vary over time is not sufficient to capture the SAD effect in daily returns: significant evidence of SAD remains in the residuals.

In light of the findings in Table 5, we estimate Eq. (17) to determine whether the price of risk varies as a function of the SAD and Fall variables. Table 6 reports the results from estimating Eq. (17).[16] We find the SAD coefficient is positive for all the countries, significantly so for all but one. The Fall coefficient estimate is everywhere significantly negative. λ_0 is significantly negative for Japan only, otherwise it is either significantly positive or insignificant.[17]

Next, to determine whether a SAD-related seasonal remains in the residuals of Eq. (17) after having allowed the price of risk to vary as a function of SAD_t and $Fall_t$, we take the residuals and regress them on SAD_t and $Fall_t$, as shown in Eq. (18). Results are provided in Table 7. We find that while the coefficient estimates on SAD_t are still positive for all markets and the coefficient estimates on $Fall_t$ are still negative for some of the indices, all estimates become insignificant. Further the magnitude of almost every estimate drops remarkably relative to Table 2, to as little as one tenth of the original magnitude. In short, the direct impact of SAD_t and $Fall_t$ on returns is virtually eliminated by allowing for time variation in market risk and the market price of risk. The implication is that trying to exploit the SAD effect would not represent a profitable trading strategy in the sense of earning abnormal risk-adjusted returns since a changing market risk premium accommodates the seasonality that arises due to the SAD and Fall variables.

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[16] We also control for Monday and tax effects and autocorrelation in returns in the estimation of Eq. (17), as shown at the top of Table 6.

[17] This set of coefficient estimates implies the price of risk is never negative for New Zealand or the US. That is, for these countries $\lambda_0+\lambda_{SAD} \cdot SAD_t$ everywhere exceeds $\lambda_{Fall} \cdot Fall_t$. For Sweden, the UK, Japan, and Australia, the price of risk may be negative for some dates. Given the significance and relative magnitudes of coefficient estimates, however, statistically significant evidence of a negative price of risk is observed only for Japan and Australia.

Table 5
Tests for the SAD effect after allowing for time variation in market risk, daily data

	US (41°N) 2/2/1962–29/12/2000	Sweden (59°N) 26/4/1989–29/12/2000	New Zealand (37°S) 1/7/1991–29/12/2000	UK (51°N) 3/1/1984–29/12/2000	Japan (36°N) 4/10/1982–29/12/2000	Australia (34°S) 7/7/1982–29/12/2000
μ^*_{SAD}	0.0237*** (2.360)	0.0393*** (2.948)	0.0270 (1.219)	0.0325*** (2.683)	0.0425 (1.198)	0.0241* (1.423)
μ^*_{Fall}	−0.0202** (−1.658)	−0.0343** (−2.018)	−0.0351* (−1.389)	−0.0405 (−1.677)	−0.0343** (−0.935)	−0.0245* (−1.296)

The table reports parameter estimates of μ^*_{SAD} and μ^*_{Fall} from the regression

$$\hat{\xi}_{it} = \mu^*_0 + \mu^*_{SAD} SAD_t + \mu^*_{Fall} Fall_t + e_{it} \tag{16}$$

where $\hat{\xi}_{it}$ is the residual return for country i after estimating Eq. (15′) on daily excess returns as shown in Table 4 (that is, after controlling for systematic risk). SAD_t is a measure based on the normalized number of hours of night in fall and winter; $Fall_t$ is an interactive dummy variable that takes the value of SAD_t from September 21 through December 20 for the US, Sweden, the UK, and Japan, the value of SAD_t from March 21 to June 20 for New Zealand and Australia, and 0 otherwise. The null hypotheses are H_0: $\mu^*_{SAD}=0$ and H_0: $\mu^*_{Fall}=0$ against the alternatives H_A: $\mu^*_{SAD}>0$ and H_A: $\mu^*_{Fall}<0$, respectively. Figures in parentheses are White (1980) heteroskedasticity-consistent t-statistics. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

Table 6
Daily time variation in market risk and the price of market risk

	US (41°N) 2/2/1962–29/12/2000	Sweden (59°N) 26/4/1989–29/12/2000	New Zealand (37°S) 1/7/1991–29/12/2000	UK (51°N) 3/1/1984–29/12/2000	Japan (36°N) 4/10/1982–29/12/2000	Australia (34°S) 7/7/1982–29/12/2000
μ	0.0245*** (5.964)	0.0172 (0.508)	−0.0118 (−1.180)	0.0276*** (2.978)	0.0174** (2.110)	0.0039 (0.626)
λ_0	0.0153** (1.918)	−0.0331 (−1.267)	0.0391** (1.805)	−0.0174 (−1.166)	−0.0186** (−2.347)	0.0081 (1.157)
λ_{SAD}	0.0307*** (5.182)	0.0220*** (5.465)	0.0198** (1.928)	0.0240*** (3.792)	0.0134** (1.945)	0.0088 (0.547)
λ_{Fall}	−0.0286*** (−3.287)	−0.0143*** (−3.772)	−0.0310* (−1.559)	−0.0146** (−1.793)	−0.0135* (−1.346)	−0.0448*** (−3.088)
ρ_1	0.1997*** (21.03)	0.1389*** (8.782)	0.1182*** (4.607)	0.0763*** (4.721)	0.0469*** (3.129)	0.1624*** (12.66)
Mon_t	−0.1107*** (−9.147)	0.0269 (0.770)	−0.1781*** (−6.524)	−0.1436*** (−3.721)	0.0487*** (2.904)	−0.0298 (−0.870)
Tax_t	0.0148 (0.422)	0.2258** (2.014)	−0.0216 (−0.205)	0.0566 (0.650)	0.0362 (0.718)	0.1737** (2.468)
ω	−0.0070*** (−11.01)	0.0179*** (2.497)	−0.0150*** (−4.523)	−0.0043 (−1.389)	0.0159*** (9.593)	−0.0367* (−1.775)
β	0.9831*** (624.21)	0.9502*** (82.152)	0.9052*** (65.46)	0.9678*** (80.10)	0.9704*** (368.26)	0.8487*** (9.353)
α	0.1429*** (36.42)	0.1921*** (6.809)	0.3097*** (6.354)	0.1676*** (5.236)	0.2550*** (45.39)	0.3469*** (2.598)
θ	−0.0851*** (−28.72)	−0.0832*** (−5.991)	−0.0569** (−1.827)	−0.0541*** (−2.747)	−0.1254*** (−31.38)	−0.1191** (−2.244)
AR	10.203	11.965	4.5669	9.5448	17.991	17.609
ARCH	10.410	2.0183	15.071	11.829	2.0183	15.071

The table reports parameter estimates from

$$r_{it} = \mu + (\lambda_0 + \lambda_{SAD}SAD_t + \lambda_{Fall}Fall_t)h_t + \rho_1 r_{it-1} + \mu_{Mon}Mon_t + \mu_{Tax}Tax_t + \eta_{it} \tag{17'}$$

$$h_t = \exp\left\{\omega + \beta\ln(h_{t-1}) + \alpha\left(\frac{|\eta_{it-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}}\right) + \theta\left(\frac{\eta_{it-1}}{\sqrt{h_{t-1}}}\right)\right\}$$

where r_{it} are daily excess returns; SAD_t is a measure based on the normalized number of hours of night in fall and winter; $Fall_t$ is an interactive dummy variable that takes the value of SAD_t from September 21 through December 20 for the US, Sweden, the UK, and Japan, the value of SAD_t from March 21 to June 20 for New Zealand and Australia, and 0 otherwise; Mon_t is a dummy variable that takes the value 1 on Mondays (or the first trading day following a long weekend) and 0 otherwise; and Tax_t is a dummy variable that takes the value 1 for the day prior to and the 4 days following the start of a tax year and 0 otherwise. One lag of the dependent variable is included to control for residual autocorrelation. (This is Eq. (17) adjusted to control for autocorrelation, Monday effects, and tax effects in returns.) The model is estimated using Quasi Maximum Likelihood methods (Bollerslev and Wooldridge, 1992) to provide t-statistics that are robust to departures from conditional normality. These robust t-statistics are reported in parentheses below the relevant parameter estimates. AR and ARCH are Lagrange multiplier tests for up to 10th-order serial correlation and ARCH in η_{it}. Both are distributed $\chi^2(10)$ under the respective null hypotheses of no serial correlation and no ARCH. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

Table 7
Tests for the SAD effect after allowing for time variation in market risk and the price of market risk, daily data

	US (41°N) 2/2/1962–29/12/2000	Sweden (59°N) 26/4/1989–29/12/2000	New Zealand (37°S) 1/7/1991–29/12/2000	UK (51°N) 3/1/1984–29/12/2000	Japan (36°N) 4/10/1982–29/12/2000	Australia (34°S) 7/7/1982–29/12/2000
μ^*_{SAD}	0.0063 (0.662)	0.0112 (0.849)	0.0100 (0.450)	0.0115 (0.930)	0.0034 (0.115)	0.0201 (1.035)
μ^*_{Fall}	−0.0030 (−0.244)	−0.0160 (−0.947)	−0.0111 (−0.440)	−0.0117 (−0.784)	0.0016 (0.044)	0.0074 (0.310)

The table reports parameter estimates of μ^*_{SAD} and μ^*_{Fall} from the regression

$$\hat{\eta}_{it} = \mu^* + \mu^*_{SAD} SAD_t + \mu^*_{Fall} Fall_t + \mu_{it} \quad (18)$$

where $\hat{\eta}_{it}$ is the daily residual return for country i after estimating Eq. (17′) on daily excess returns as shown in Table 6 (that is, after controlling for systematic risk). SAD_t is a measure based on the normalized number of hours of night in fall and winter; $Fall_t$ is an interactive dummy variable that takes the value of SAD_t from September 21 through December 20 for the US, Sweden, the UK, and Japan, the value of SAD_t from March 21 to June 20 for New Zealand and Australia, and 0 otherwise. The null hypotheses are H_0: μ^*_{SAD} =0 and H_0: μ^*_{Fall} =0 against the alternatives H_A: μ^*_{SAD} >0 and H_A: μ^*_{Fall} <0, respectively. Figures in parentheses are White (1980) heteroskedasticity-consistent t-statistics. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

Table 8
Monthly time variation in market risk and the price of market risk

	US (41°N) 7/1926–12/2000	Sweden (59°N) 1/1975–12/2000	New Zealand (37°S) 7/1991–12/2000	UK (51°N) 2/1984–12/2000	Japan (36°N) 2/1960–12/2000	Australia (34°S) 8/1982–12/2000
μ	0.3478*** (2.519)	1.1659*** (4.512)	−1.2725*** (−3.086)	2.5726** (2.858)	0.1053 (0.257)	0.4101 (0.806)
λ_0	0.0072** (1.771)	−0.0528* (−1.503)	0.0362** (1.892)	−0.1299** (−2.499)	−0.0177 (−0.880)	−0.0198 (−0.656)
λ_{SAD}	0.0104*** (3.205)	0.02356*** (6.758)	0.0326** (2.016)	0.0236* (1.649)	0.0478*** (4.295)	0.0372* (1.668)
λ_{Fall}	−0.0013 (−0.302)	−0.0142*** (−3.485)	−0.0437** (−2.122)	−0.0039 (−0.022)	−0.0394*** (−3.313)	−0.0461* (−1.582)
ρ_1	0.0706** (2.180)	0.1136* (1.598)	−0.1391* (−1.509)	0.0166 (0.221)	0.0060 (0.129)	−0.0514 (−0.735)
ω	0.1220*** (29.71)	0.5886*** (38.14)	0.6064*** (12.81)	0.1512* (1.910)	0.1359 (0.981)	0.0142*** (3.738)
β	0.9620*** (771.8)	0.8311*** (190.9)	0.7962*** (49.45)	0.9480*** (37.56)	0.9596*** (22.47)	0.9918*** (190.3)
α	0.2197*** (7.450)	0.3116*** (5.249)	0.3809** (1.934)	−0.0164 (−0.203)	0.1967*** (3.505)	−0.1209*** (−2.640)
θ	−0.0724*** (−4.243)	0.0062 (0.199)	−0.0046 (−0.050)	0.1333*** (3.285)	−0.0433 (−1.107)	0.0238 (0.933)
AR	12.650	3.1511	6.6347	10.624	6.3248	10.055
ARCH	9.3341	5.3421	12.298	9.2601	9.7184	1.9759

The table reports parameter estimates from

$$r_{it} = \mu + (\lambda_0 + \lambda_{SAD} SAD_t + \lambda_{Fall} Fall_t) h_{it} + \rho_1 r_{it-1} + \eta_{it} \tag{17''}$$

$$h_{it} = \exp\left\{ \omega + \beta \ln(h_{it-1}) + \alpha \left(\frac{|\eta_{it-1}|}{\sqrt{h_{it-1}}} - \sqrt{\frac{2}{\pi}} \right) + \theta \left(\frac{\eta_{it-1}}{\sqrt{h_{it-1}}} \right) \right\}$$

where r_{it} are monthly excess returns. SAD_t is a measure based on the normalized median monthly number of hours of night in fall and winter; $Fall_t$ is an interactive dummy variable that takes the value of SAD_t from October December for the US, Sweden, the UK, and Japan, the value of SAD_t from April through June for New Zealand and Australia, and 0 otherwise. One lag of the dependent variable is included to control for residual autocorrelation. (This is Eq. (17) adjusted to control for autocorrelation.) The model is estimated using Quasi Maximum Likelihood methods (Bollerslev and Wooldridge, 1992) to provide t-statistics that are robust to departures from conditional normality. These robust t-statistics are reported in parentheses below the relevant parameter estimates. AR and ARCH are Lagrange multiplier tests for up to 12th-order serial correlation and ARCH in ξ_{it}. Both are distributed $\chi^2(12)$ under the respective null hypotheses of no serial correlation and no ARCH. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

Table 9

Tests for SAD and fall effects after allowing for time variation in market risk and the price of market risk, monthly data

	US (41°N) 7/1926–12/2000	Sweden (59°N) 1/1975–12/2000	New Zealand (37°S) 7/1991–12/2000	UK (51°N) 2/1984–12/2000	Japan (36°N) 2/1960–12/2000	Australia (34°S) 8/1982–12/2000
μ^*_{SAD}	0.0009 (0.043)	−0.0116 (−0.420)	0.1715 (0.320)	−0.0803 (−0.251)	−0.1811 (−0.458)	0.1980 (0.391)
μ^*_{Fall}	−0.0176 (−0.078)	0.1381 (0.492)	−0.0472 (−0.071)	−0.0285 (−0.085)	0.1381 (0.800)	0.0237 (0.049)

The table reports parameter estimates of μ^*_{SAD} and μ^*_{Fall} from the regression

$$\hat{\eta}_{it} = \mu^* + \mu^*_{SAD}\, SAD_t + \mu^*_{Fall}\, Fall_t + \mu_{it} \qquad (18)$$

where $\hat{\eta}_{it}$ is the monthly residual return for country i after estimating Eq. (17′) on monthly returns as shown in Table 8 (that is, after controlling for systematic risk). SAD_t is a measure based on the normalized median monthly number of hours of night in fall and winter; $Fall_t$ is an interactive dummy variable that takes the value of SAD_t from October December for the US, Sweden, the UK, and Japan, the value of SAD_t from April through June for New Zealand and Australia, and 0 otherwise. The null hypotheses are H_0: $\mu^*_{SAD}=0$ and H_0: $\mu^*_{Fall}=0$ against the alternatives H_A: $\mu^*_{SAD}>0$ and H_A : $\mu^*_{Fall}<0$, respectively. Figures in parentheses are White (1980) heteroskedasticity-consistent t-statistics. *, ** , and *** denote significance at the 10%, 5%, and 1% levels, respectively, based on one-sided t-tests.

3.2. Results using monthly excess returns

The results from estimating Eq. (17) using monthly excess returns are reported in Table 8.[18] As in Table 6 (the same estimation using daily data), there is no evidence of autocorrelation or ARCH in any of the markets, and the EGARCH estimates are typically significant and appropriately signed. The null that $\lambda_{SAD}=0$ is rejected for all of the markets: risk aversion increases with SAD. λ_{Fall} is negative for all the markets, significantly so for all but the US and the UK. λ_0 is significantly positive for the US and New Zealand, but negative for Sweden, the UK, Japan, and Australia, some significantly.[19]

Turning to Table 9, in which we test for evidence of SAD effects in the residuals from the monthly regression displayed in Table 8, we find that the conditional CAPM with λ_t specified as a parametric function of SAD_t and $Fall_t$ purges SAD effects from the residuals. The coefficient estimates on the SAD and Fall variables are insignificant for all cases in Table 9. Overall, it appears that allowing for time variation in market risk and the price of risk captures the SAD seasonal effect in stock returns documented by KKL. As we only consider SAD_t and $Fall_t$ as instruments in Eq. (17), there remains the possibility that our findings may be fragile to the inclusion of other instruments for the time-varying market price of risk. We postpone for future study an exploration of the robustness of the SAD effect to the inclusion of variables such as the lagged interest rate, dividend yield, and exchange rates.

4. Conclusion

The association between seasonal variation in daylight and depression is known to medical practitioners as seasonal affective disorder, or SAD. Studies in psychology have shown that depressed individuals, such as those afflicted with SAD, experience heightened risk aversion. We build on past research in finance which documents a link between the depression (and hence increased risk aversion) individuals experience as a consequence of SAD and the seasonalities that are observed in international stock market returns. We explore the link between seasonal depression and market returns, known as the SAD effect, in the context of a conditional CAPM framework. We study stock market returns at daily and monthly frequencies for several countries: the US, Japan, the UK, and Sweden in the Northern Hemisphere, and New Zealand and Australia in the Southern Hemisphere (where the patterns of daylight and hence the timing of seasonal depression are 6 months out of phase relative to the Northern Hemisphere). Results in all six markets suggest that the SAD effect is fully captured by a model which allows for time variation in market risk and a time-varying price of risk. An attractive feature of this result given

[18] Although we do not report the results here to conserve space, we also estimated Eqs. (15) and (16) using monthly data. The results are qualitatively identical to those reported for daily data in that there is strong evidence of a SAD seasonal.

[19] Based on these results, we see that for the US, the price of risk is always positive. For the other countries, the price of risk is estimated to be negative for parts of the year, suggesting a limitation of the simple CAPM specification.

the model we use is that the price of risk can be interpreted as a weighted average of agents' coefficients of relative risk aversion, the weight being the individual agent's proportion of wealth. That is, the SAD effect may well be a natural consequence of changes in risk aversion over time.

Acknowledgements

We have benefited from the comments and suggestions of the editor, Franz Palm, the associate editor, and two referees. A previous version of this paper was circulated with the title "A SAD Day for Behavioral Finance? Winter Blues and Time Variation in the Price of Risk." We are grateful for valuable conversations with Kris Jacobs, Maurice Levi, Cesare Robotti, participants at the European Finance Association 2003 meeting, the Northern Finance Association 2003 meeting and seminar participants at the Federal Reserve Bank of Atlanta, The University of Manchester, and the University of Münster. Kramer thanks the Social Sciences and Humanities Research Council of Canada for financial support. Much of this research was done while Garrett was a visitor at and while Kamstra was an economist at the Federal Reserve Bank of Atlanta. They would like to thank the Bank for its research support. The views expressed in this paper are those of the authors and not necessarily those of the Federal Reserve Bank of Atlanta or the Federal Reserve System. All remaining errors are the sole responsibility of the authors.

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