2. Seasonality in stock returns and government bond returns

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1 INTRODUCTION

In seeking to understand time variation in the rates of return earned by those who invest in financial securities, researchers have uncovered various empirical regularities. Some are seasonal in nature, tending to occur on a deterministic schedule. These include stock market regularities such as the Monday effect (see French, 1980; Gibbons and Hess, 1981; Rogalski, 1984), the tax-year effect (Rozeff and Kinney, 1976), and the daylight saving effect (Kamstra et al., 2000). Others arise non-deterministically, for example depending on random weather events (Saunders, 1993; Hirshleifer and Shumway, 2003) or the outcome of championship sports competitions (Edmans et al., 2007).

The focus of this chapter is a regularity of the former category, arising on average on a deterministic schedule based on predictable daylight exposure through the seasons, and affecting financial markets evidently by altering investors' moods and risk aversion. This regularity has come to be known as the seasonal affective disorder (SAD) effect. The underlying hypothesis is that, beginning around autumn, as the length of daylight shortens in non-equatorial locations, people tend to become more despondent, their moods even reaching the threshold for clinical depression among a subset of individuals. Medical research, including that by Rosenthal et al. (1984) and Lam (1998), documents the relationship between seasonality in daylight exposure and seasonality in people's moods. In turn, experimental research by Kramer and Weber (2012) shows the relationship between seasonality in people's moods and seasonality in their financial risk preferences. Overall, during the seasons when the amount of daylight at a given location is below the annual average, most individuals tend to be relatively more depressed and relatively more risk averse than they are during the rest of the year.

The implications of these relationships for financial markets have been extensively documented. Kamstra et al. (2003) examine stock market index returns for nine countries at various latitudes in both hemispheres, and find statistically significant and economically large differences in returns across the seasons consistent with investors' risk preferences varying with daylight exposure. Investors appear to demand a higher risk premium during seasons when daylight exposure is reduced, the result of which is that the equity risk premium in the US is about 6% higher per annum during the fall/winter seasons than in spring/summer. The amplitude of seasonal return variation is relatively greater for equity markets located at higher latitudes versus those closer to the equator, and the timing of the seasonality in returns is offset by six months in southern hemisphere countries relative to northern hemisphere countries, just like the seasons. More recent studies have documented an equity market SAD effect for larger groups of countries (see Dowling and Lucey, 2008; Kamstra et al., 2012).

For a regularity rooted in seasonally varying investor risk aversion, a reasonable question is whether it may also apply to securities other than equities. Kamstra et al. (2015) examine US Treasury securities and find statistically significant and economically large seasonality in government bond returns consistent with the SAD effect. Specifically, during the fall and winter seasons, when investors tend to be more risk averse, Treasury bond returns are on average lower than during spring and summer. The difference between the peak and trough in average monthly annualized government bond returns is about 80 basis points, which is large relative to the unconditional average return for this exceptionally safe investment class. Essentially, government bond investors demand a lower bond return during those seasons when they experience higher than average risk aversion.

Turning to investment *quantities* as opposed to security rates of return, Kamstra et al. (2017) consider the flow of investor funds into and out of mutual funds in the US, Canada, and Australia. As the authors show, mutual fund flows are dominated by the decisions of retail investors, not large institutional investors, and so mutual fund flows plausibly reveal portfolio reallocation decisions of retail investors. Kamstra et al. (2017) find that flows into and out of risky versus safe mutual funds are consistent with retail investors experiencing seasonal variation in risk aversion due to seasonal variation in daylight. Aggregate fund flows are such that, on average, these investors prefer safe mutual funds in the fall and risky mutual funds in spring. After controlling for other known influences on mutual fund flows, in the month of September the typical magnitude of flows out of risky funds is $13 billion, while the typical magnitude of flows into safe funds is US$3 billion (flows into cash holdings like bank accounts make up much of the difference). The directions of these flows are then reversed in spring.

Additional key papers on the SAD effect include the following: Garrett et al. (2005) document SAD-related seasonal variation in the price of risk in the context of a conditional version of the capital asset pricing model estimated using equity market index data for the US, Sweden, New Zealand, the UK, Japan, and Australia; and Kamstra et al. (2014) find that plausible magnitudes of seasonal changes in risk aversion are able to generate the observed magnitudes of seasonal changes in equity and government bond returns in the US in the context of a consumption-based asset pricing model.

In this chapter, we take a deep dive into seasonality as it arises in equity markets and government bond markets. Our novel contributions include: consideration of the broadened selection of maturities of government bond returns for the US; the first-ever analysis of the SAD effect in equity returns across *size-sorted deciles* for the US, Canada, the UK, Germany, and Australia; the first-ever consideration of the SAD effect based on *disaggregated firm-by-firm stock return data* for the US, Canada, the UK, Germany, and Australia; and the development of a new proxy for the SAD effect based on Google searches (supplementing the existing measure based on clinical onset of and recovery from symptoms among SAD patients). We also present international evidence on the weakening of the Monday effect and tax-year effect over time.

2 DATA

Our initial analysis focuses on daily US value-weighted size-sorted decile stock returns retrieved from Ken French's data library;[1] daily value-weighted size-sorted decile stock return data for Canada, Germany, the UK, and Australia compiled from Datastream firm-level return data; and monthly 2-, 5-, 7-, 10-, 20-, and 30-year US Treasury note and bond return data sourced from the Center for Research in Security Prices (CRSP).[2] We end all of our data samples before the year 2020 to avoid price volatility associated with the Covid-19 pandemic. The US equity data series starts on January 2, 1926; the international data series starts on January 1, 1990 because there are very few firms with complete data available prior to 1990; and the Treasury bond data start in January 1972 because, until 1971, notes and bonds were offered only in fixed-price sales (see Garbade, 2007).[3] We perform additional tests using *firm-level* daily US and international stock return data, making use of fixed effects for firm and year, with standard errors clustered by firm and day. We measure the SAD effect initially using the clinical onset of and recovery from seasonal depression developed by Kamstra et al. (2015), and later using a new instrument we develop based on Google search data.

Table 2.1 contains summary statistics for daily value-weighted size-sorted decile stock return data and monthly government bond return data, and Table 2.2 contains summary statistics for firm-level stock return data. In Table 2.1 we see that mean stock returns and volatility are generally higher for smaller firms (Decile 1 corresponds to the smallest firms), with daily mean decile stock returns in the range of 2–25 basis points and volatility around 1 or 2% for all the countries. In Table 2.2, the firm-level summary statistics reveal much higher share volume and daily mean returns for US firms than for other countries, as well as roughly ten times the number of firm/day observations.

Table 2.1 Summary statistics

Series	N	Mean	Std. Dev.	Min.	Max.
US 30-Year Treasury	576	0.671	3.54	−14.738	17.220
US 20-Year Treasury	576	0.685	3.06	−10.593	15.235
US 10-Year Treasury	576	0.600	2.20	−6.682	9.999
US 7-Year Treasury	576	0.605	1.90	−7.039	10.749
US 5-Year Treasury	576	0.557	1.54	−5.802	10.612
US 2-Year Treasury	576	0.486	0.86	−3.695	8.420
US 1-Year Treasury	576	0.459	0.56	−1.721	5.606
US 90-Day Treasury	576	0.412	0.32	−0.013	2.131
US 30-Day Treasury	576	0.376	0.29	−0.004	1.516
US Decile 1	25010	0.107	2.44	−34.300	120.990
US Decile 2	25010	0.099	2.26	−33.280	93.340
US Decile 3	25010	0.101	2.08	−31.120	75.960
US Decile 4	25010	0.097	1.98	−31.500	67.470
US Decile 5	25010	0.093	1.90	−30.450	56.240
US Decile 6	25010	0.095	1.83	−32.380	59.820
US Decile 7	25010	0.090	1.76	−30.030	52.150
US Decile 8	25010	0.088	1.71	−31.060	53.200
US Decile 9	25010	0.083	1.64	−32.360	46.860
US Decile 10	25010	0.074	1.50	−28.000	35.170
Canada Decile 1	7565	0.104	1.13	−9.248	45.355
Canada Decile 2	7552	0.045	0.88	−17.143	10.360

Table 2.1 (continued)

Series	N	Mean	Std. Dev.	Min.	Max.
Canada Decile 3	7555	0.044	0.93	−27.610	16.682
Canada Decile 4	7554	0.041	0.85	−10.969	7.968
Canada Decile 5	7552	0.035	0.89	−13.045	9.091
Canada Decile 6	7556	0.035	0.93	−10.381	9.760
Canada Decile 7	7555	0.029	0.91	−8.940	7.145
Canada Decile 8	7554	0.034	0.90	−9.226	8.605
Canada Decile 9	7553	0.038	0.86	−7.007	7.800
Canada Decile 10	7551	0.038	0.99	−9.569	9.635
Germany Decile 1	7583	0.062	1.39	−12.528	18.382
Germany Decile 2	7581	0.039	1.22	−9.474	24.282
Germany Decile 3	7581	0.021	1.10	−8.893	11.037
Germany Decile 4	7581	0.027	1.08	−7.027	11.702
Germany Decile 5	7581	0.028	1.12	−10.297	9.464
Germany Decile 6	7581	0.033	1.11	−10.527	10.881
Germany Decile 7	7581	0.039	1.15	−10.558	11.504
Germany Decile 8	7581	0.056	1.22	−10.642	12.835
Germany Decile 9	7581	0.048	1.16	−8.179	11.825
Germany Decile 10	7581	0.030	1.33	−9.206	17.348
UK Decile 1	7581	0.069	2.29	−5.283	188.220
UK Decile 2	7580	0.035	0.69	−5.960	5.488
UK Decile 3	7580	0.034	0.67	−6.744	5.443
UK Decile 4	7580	0.049	0.68	−5.211	5.228
UK Decile 5	7580	0.038	0.75	−7.704	8.184
UK Decile 6	7580	0.039	0.83	−7.757	7.526
UK Decile 7	7580	0.048	0.93	−8.674	9.657
UK Decile 8	7580	0.045	0.97	−8.125	8.496
UK Decile 9	7580	0.045	1.05	−7.155	8.929
UK Decile 10	7580	0.036	1.08	−8.805	9.935
Australia Decile 1	7593	0.093	0.87	−10.992	6.729
Australia Decile 2	7591	0.066	0.79	−10.811	7.669
Australia Decile 3	7591	0.051	0.81	−14.591	7.116
Australia Decile 4	7591	0.044	0.85	−8.809	8.521
Australia Decile 5	7591	0.051	0.90	−10.287	8.049
Australia Decile 6	7592	0.048	0.94	−9.536	7.764
Australia Decile 7	7591	0.045	0.94	−9.152	6.401
Australia Decile 8	7591	0.042	0.93	−8.891	6.992
Australia Decile 9	7591	0.041	0.92	−8.130	6.601
Australia Decile 10	7591	0.040	0.99	−8.377	7.170

Notes:
The sample period for monthly Treasury returns is January 1972–December 2019; for US daily size-sorted decile stock returns January 1926–December 2019; and for international daily size-sorted decile stock returns January 1990–December 2019.

In all cases: Equity returns are value weighted; Decile 1 corresponds to the smallest firms and Decile 10 to the largest; returns are expressed as percentages.

Table 2.2 Summary statistics calculated on means of variables firm-by-firm, January 1990–December 2019

Country & Variable	N	Mean	Std. Dev.	Median	Skew.	Kurt.	Min.	Max.
US								
Share Price (USD)	41434787	22.140	16.349	19.37	4.33	45.36	5.00	454.96
Volatility	39417381	0.039	0.035	0.03	1.68	13.08	0.00	0.54
Log Volume (shares/1000)	40553502	10.387	10.451	2.11	–0.06	–0.39	1.77	17.77
Mkt. Cap. (USD billions)	41434787	1.370	0.193	7.08	18.52	491.11	0.00	279.56
Return (%)	41416936	0.117	0.071	0.49	32.76	2271.63	–9.22	40.55
Canada								
Share Price (USD)	5582327	40.194	5.644	511.75	19.41	408.22	1.05	12975.24
Volatility	4855390	3.776	3.562	1.96	1.50	7.43	0.30	25.25
Log Volume (shares/1000)	5579699	2.682	2.529	1.87	0.38	–0.19	–1.78	10.70
Mkt. Cap. (USD billions)	5579699	0.625	0.106	2.53	9.41	110.95	0.00	47.22
Return (%)	5582327	0.003	0.044	0.29	2.54	123.03	–3.80	7.27
Germany								
Share Price (USD)	4400776	39.022	14.584	97.43	10.48	182.56	1.09	2428.62
Volatility	4002602	4.357	3.789	2.36	2.05	9.29	0.23	28.94
Log Volume (shares/1000)	4398498	1.074	0.767	1.81	1.16	1.84	–2.10	9.37
Mkt. Cap. (USD billions)	4398498	1.715	0.112	6.82	7.28	61.85	0.00	84.76
Return (%)	4400776	–0.024	0.041	0.42	0.01	24.94	–2.97	4.87
UK								
Share Price (USD)	5015967	8.210	2.718	131.99	36.11	1342.69	1.00	5232.22
Volatility	4490366	2.783	2.512	1.43	4.11	46.55	0.43	26.40
Log Volume (shares/1000)	5013184	3.826	3.472	2.07	0.46	–0.06	–1.90	11.26
Mkt. Cap. (USD billions)	5013184	1.275	0.186	5.99	13.19	222.90	0.00	126.48
Return (%)	5015967	–0.008	0.031	0.34	19.01	771.24	–2.74	13.68
Australia								
Share Price (USD)	2107727	4.763	1.822	13.06	6.51	50.15	1.01	165.56
Volatility	1897210	2.966	2.636	1.46	1.71	7.10	0.19	16.85
Log Volume (shares/1000)	2107000	4.427	4.452	2.18	–0.13	–0.33	–2.09	10.55
Mkt. Cap. (USD billions)	2107000	0.877	0.231	3.02	10.89	150.98	0.00	55.41
Return (%)	2107727	0.003	0.034	0.28	–3.00	57.92	–4.53	2.89

Notes: Volatility is calculated using daily high/low prices: Volatility = 200 * (High – Low) / (High + Low). These summary statistics are calculated in a two-step fashion. First, for each firm, the mean share price, volatility, etc. are calculated. The statistics are then calculated such that, for example, the reported median is the average median over firms.

3 ANALYSIS

Here we estimate the SAD effect in the US equity and government bond data and in the international equity data, controlling for established regularities.

3.1 Evidence Based on US Size-Sorted Decile Stock Return and Government Bond Return Data

For the US equity data, the model we estimate is:

$$r_{i,t} = \alpha_i + \beta_{i,\text{Mon}} \cdot \text{Mon}_t + \beta_{i,\text{Tax}} \cdot \text{Tax}_t + \beta_{i,\text{OR}} \cdot \text{OR}_t + \epsilon_t, \tag{2.1}$$

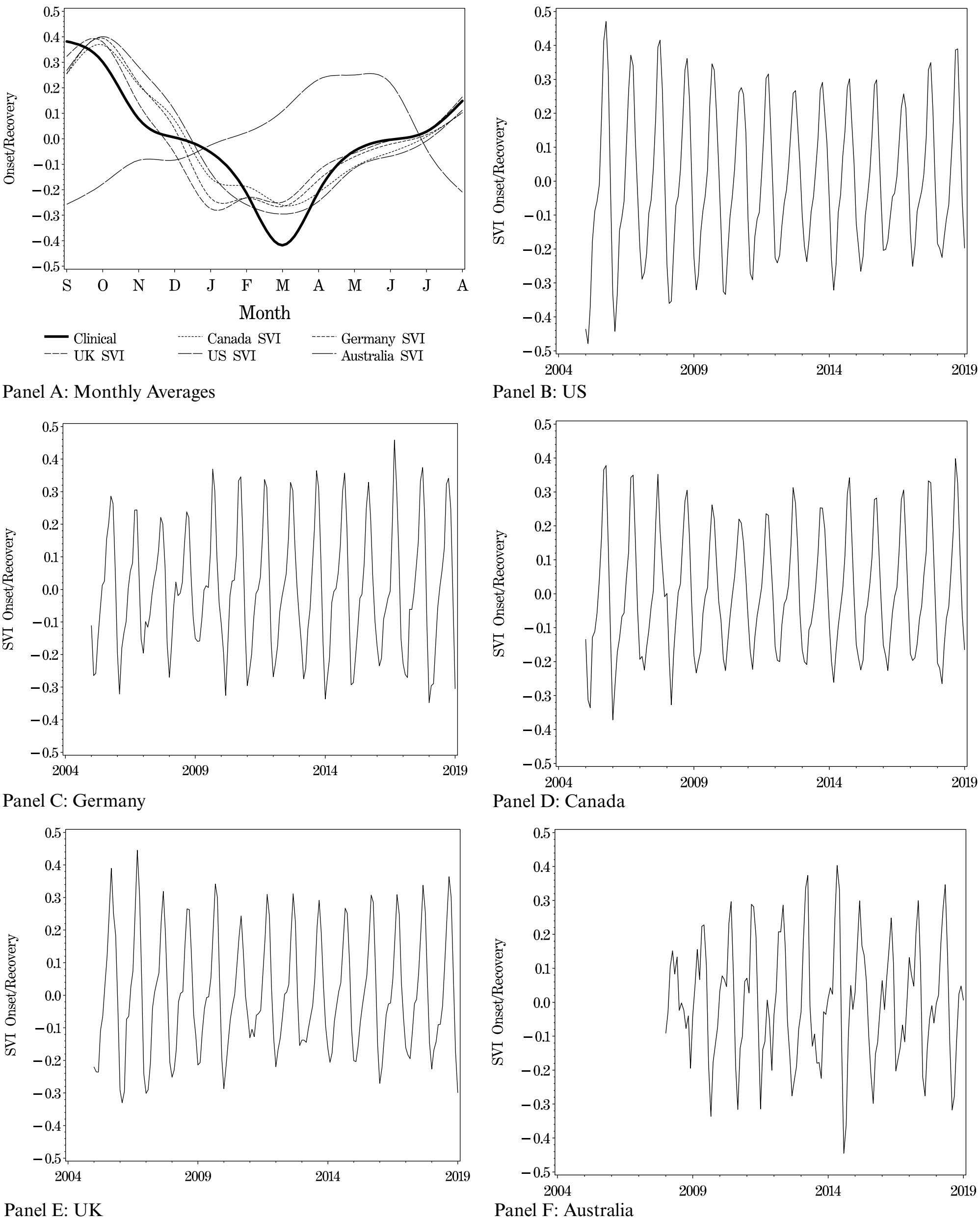
where r_t is the daily return for a given equity return series indexed by i; OR_t is the SAD onset/recovery variable from Kamstra et al. (2015);[4] Mon_t is an indicator variable for trading days that occur on a Monday; Tax_t is an indicator variable set to equal one for trading days in the first month of the tax year (January for the US); ϵ is a disturbance term; and i ranges from 1 to 10 in the case of decile regressions. We estimate the model as a panel/time-series regression with MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors.

Before we turn to the regression results, we wish to enable economic interpretation of the coefficient estimate on the SAD onset/recovery variable by examining the variable itself in greater detail. Panel A of Figure 2.1 contains a plot of the SAD onset/recovery variable, represented as a thick solid line. (We consider other the series plotted in Panel A and Panels B–F later.) The SAD onset/recovery variable represents the *change in the proportion of people actively suffering from seasonal depression* at a given point in time. It is positive when (on balance) people are succumbing to symptoms and negative when (on balance) people are recovering. With SAD-sufferers tending to first experience seasonal depression after the summer solstice, the SAD onset/recovery variable assumes a small positive value beginning around July. The variable then increases in magnitude to a peak around the autumn equinox and declines to around zero around the winter solstice, at which point a small fraction of SAD-sufferers begin recovering from seasonal depression. This leads to a negative value for the SAD onset/recovery variable beginning in January, reaching an annual low around the spring equinox and then rising back to zero around the summer solstice.

Panel A of Table 2.3 contains regression results for the daily US value-weighted size-sorted decile equity returns. The SAD onset/recovery coefficient estimates, $\hat{\beta}_{\text{OR}}$, are uniformly negative across deciles, which indicates that the SAD effect is associated with relatively lower equity returns in summer/fall and relatively higher equity returns in winter/spring. This is consistent with equity returns being influenced by seasonally varying risk aversion arising due to seasonally varying length of day. The SAD onset/recovery coefficient estimates are generally larger for smaller (riskier) firms and are significant with t-test statistics ranging from 2.0 to 2.5, with the single exception of the onset/recovery coefficient for the largest decile. An (untabulated) joint test of significance of the onset/recovery coefficient estimates across deciles has a p-value less than 0.1%, indicative of a significant SAD effect for the US equity market overall. The Monday and tax-year coefficient estimates are also strongly significant and are similarly larger in magnitude for smaller firm-size deciles.

For the US government bond return data, the model we estimate is:

$$r_{i,t} = \alpha_i + \beta_{i,\text{OR}} \cdot \text{OR}_t + \epsilon_t, \tag{2.2}$$



Notes:
Panel A: The thick solid line ("Clinical") is the monthly SAD onset/recovery variable developed by Kamstra et al. (2015). The dotted lines represent the monthly average of the full time-series of country-specific Google SVI SAD onset/recovery proxies in Panels B–F.

Panel B: This plots the Google SVI onset/recovery proxy for the US.

Panels C–F: These plot the Google SVI onset/recovery proxy for Germany, Canada, the UK, and Australia respectively.

Figure 2.1 SAD onset/recovery measures

Table 2.3 Regression results based on US size-sorted decile equity returns and government bond returns

Panel A: US Size-Sorted Decile Equity Returns										
Decile → Statistic ↓	1	2	3	4	5	6	7	8	9	10
β_{OR}	−.10	−.10	−.09	−.08	−.08	−.08	−.08	−.07	−.07	−.05
Std. Err.	.039	.041	.039	.038	.038	.036	.037	.036	.035	.034
t-test	−2.5	−2.3	−2.4	−2.1	−2.2	−2.2	−2.3	−2.0	−2.0	−1.6
p-value	.007	.010	.009	.018	.014	.013	.010	.024	.025	.058
β_{Mon}	−.26	−.25	−.24	−.23	−.23	−.22	−.23	−.21	−.19	−.15
Std. Err.	.022	.023	.022	.021	.021	.020	.020	.020	.019	.019
t-test	−12	−11	−11	−11	−11	−11	−11	−11	−9.9	−7.9
p-value	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
β_{Tax}	.276	.161	.131	.100	.085	.068	.052	.036	.037	.002
Std. Err.	.028	.027	.026	.025	.024	.023	.023	.023	.022	.022
t-test	9.73	5.98	5.08	4.06	3.48	2.90	2.27	1.61	1.67	.095
p-value	.000	.000	.000	.000	.000	.002	.011	.054	.047	.462
R^2	.0105	.0070	.0066	.0063	.0065	.0058	.0064	.0055	.0049	.0030

Table 2.3 (continued)

Panel B: US Government Bond Returns

Maturity→ Statistic ↓	30-year	20-year	10-year	7-year	5-year	2-year
β_{OR}	1.59	1.22	1.11	1.01	.908	.435
Std. Err.	.668	.581	.431	.349	.290	.167
t-test	2.38	2.10	2.58	2.89	3.13	2.60
p-value	.009	.018	.005	.002	.001	.005
R^2	.0090	.0071	.0114	.0126	.0155	.0114

Notes:
Panel A results are based on estimating Equation (2.1) using US value-weighted size-sorted decile return data in a panel/time-series model for January 1926–December 2019.

β_{OR} is the coefficient estimate on the SAD onset/recovery variable developed by Kamstra et al. (2015); β_{Mon} is an indicator variable set to equal one if a trading day occurs on a Monday; and β_{Tax} is an indicator variable set to equal one if a trading day occurs in the first month of the US tax year, January.
Panel B results are based on estimating Equation (2.2) using US government bond return data in a panel/time-series model for January 1972–December 2019.
Decile 1 is the smallest firm-size decile and Decile 10 is the largest.

In all cases, we calculate standard errors using MacKinnon and White's (1985) bootstrap heteroskedasticity-consistent method. We omit the intercept from the tabulated results for brevity.

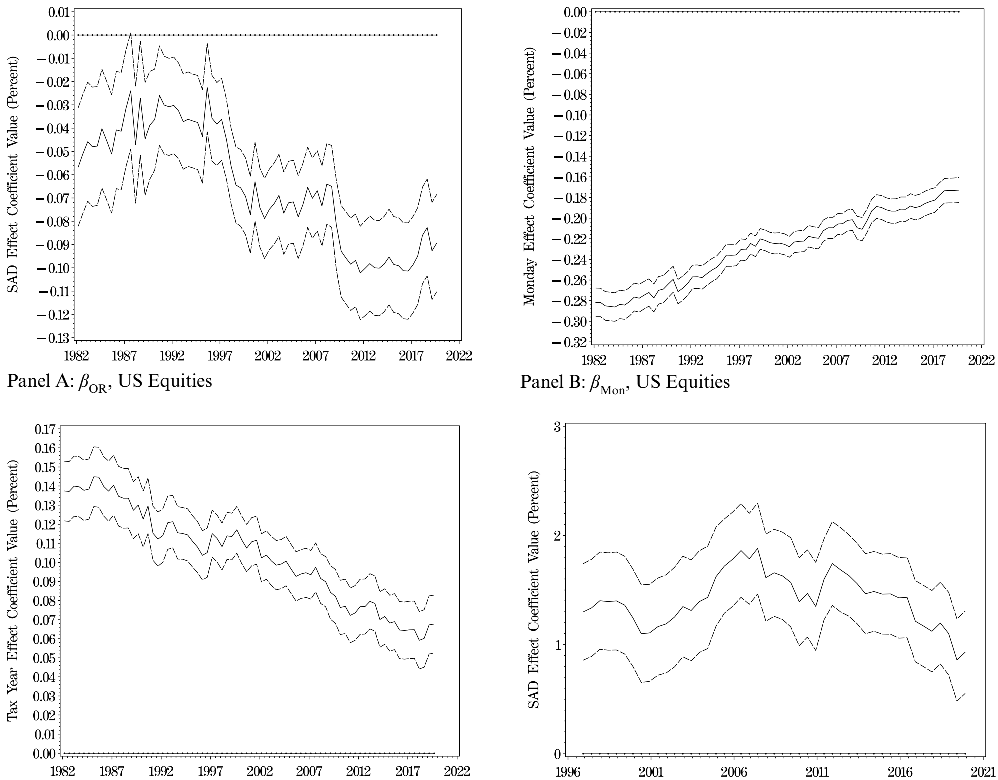
where r_t is the monthly return for a given Treasury bond series indexed by *i* (for the 2-, 5-, 7-, 10-, 20-, and 30-year maturities), OR_t is the SAD onset/recovery variable from Kamstra et al. (2015), and ϵ is a disturbance term. We estimate the model as a panel/time-series regression with MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors. For simplicity we include only the SAD onset/recovery as an explanatory variable; we find qualitatively identical results if we include additional controls, consistent with Kamstra et al. (2015), who consider alternative regression model specifications for estimating the SAD effect in Treasury notes and bonds.

Panel B of Table 2.3 contains regression results for the monthly US Treasury return regressions.[5] The SAD onset/recovery coefficient estimates generally decline from the longest to the shortest Treasury maturities. Each is strongly statistically significant, as is an (untabulated) joint test of significance of the coefficients across maturities. The coefficient estimate for the SAD effect for Treasury returns is positive, in contrast to the negative coefficient estimate observed for equity returns. This suggests that the SAD effect has a different seasonal influence on Treasuries relative to equities: in the fall, when the SAD effect is associated with relatively lower equity returns, the marginal effect on Treasuries is positive; and in the new year, when the SAD effect is associated with relatively higher equity returns, the marginal effect on Treasuries is negative. These findings are consistent with seasonally varying investor preferences being such that the reduced daylight in the fall leads to greater risk aversion (and greater relative preference for safer securities) than in winter/spring.

Figure 2.2 depicts the stability of key regression model coefficient estimates over rolling-window subsets of the full sample periods for the US equity and government bond data. Consider first Panels A–C, which are based on US equity return regressions. To produce the plots in Panels A–C we estimate Equation (2.1) sequentially using rolling windows of 60 years of US daily value-weighted size-sorted decile equity return data at a time, updated every 126 days, over the full sample period (January 1926 to December 2019). For ease of plotting, we constrain each of the model coefficients (SAD onset/recovery, Monday, and tax-year) to be the same across the ten size-sorted deciles. Panels A–C contain the rolling-window estimates of β_{OR}, β_{Mon}, and β_{Tax}, respectively. Notice from Panel A that the rolling onset/recovery coefficient estimates are consistently negative and significant, generally taking on larger negative values in more recent decades. The Monday effect has been consistently negative and significant over the full sample, appearing to become somewhat diminished over time. The tax-year effect has been consistently positive and significant over the full sample, also appearing to diminish over time.

Turning to Panel D of Figure 2.2—the case of the Treasury returns data—to produce the plot, we estimate Equation (2.2) on a rolling-window basis using 25 years of monthly bond data at a time, updated every six months, over the full sample period (January 1972 to December 2019). Again, for ease of plotting, we constrain the SAD onset/recovery coefficient estimate to be the same across all the Treasury bond maturities. We see in Panel D that the coefficient estimate is uniformly positive for Treasuries across all subsamples. (Recall that the equity returns are daily and the Treasury returns are monthly, so the scale of the SAD onset/recovery coefficients in Panel A versus D is not directly comparable.)

Overall, the sign of the SAD effect is opposite for equities versus Treasuries; and, while the magnitude of the effect varies somewhat over time, it is reliably negative (positive) for equities (Treasuries), and typically very strongly significant at conventional



Panel A: β_{OR}, US Equities

Panel B: β_{Mon}, US Equities

Panel C: β_{Tax}, US Equities

Panel D: β_{OR}, US Treasurys

Notes:
Panels A, B, and C: coefficient estimates for the SAD onset/recovery variable, Monday effect, and tax-year effect, respectively, based on rolling periods of roughly 60 years of US value-weighted daily decile returns data at a time, with estimates updated every 126 periods. The three estimates are constrained to be equal across deciles.

Panel C: coefficient estimates for the SAD onset/recovery variable based on rolling windows of 25 years of US monthly government bond return data, with estimates updated every 6 months. This estimate is constrained to be equal across the 30-, 20-, 10-, 7-, 5-, and 2-year maturities.

Panels A–D: dashed lines represent a 90% confidence interval around the coefficient estimates.

Figure 2.2 Coefficient estimates for US equity and Treasury return rolling-window regressions

significance levels. As we can see from Figure 2.2, however, the tax loss selling and Monday effects have been shrinking over time.

3.2 Evidence Based on International Size-Sorted Decile Equity Return Data

We consider now size-sorted decile equity return data for Australia, Canada, Germany, and the UK. This selection of countries reflects a range of latitudes which may be helpful for identification, considering that the SAD effect arises due to seasonality in daylight exposure, and hence should vary in intensity depending on the latitude and hemisphere of a given population. The mean center of population is approximately 37°N for the US, 48°N for Canada, 51°N for Germany, and 53°N for the UK. Because variations in daylight are more extreme in higher-latitude locations, we expect stronger SAD effects in the UK, Germany, and Canada than in the US. For Australia, the mean center of population is about 34°S. Because the seasons are offset by six months in the southern hemisphere, we expect the SAD effect to be likewise offset.

The regression model we use for the international equity return data is Equation (2.1) with some explanatory variables modified as follows. The tax year begins in April in the UK and July in Australia, and hence the tax-year indicator variable is set to one for trading days in April in the UK and July in Australia. We shift SAD onset/recovery by six months for Australia to account for the fact that in the southern hemisphere the seasons are six months out of phase relative to the northern hemisphere. The decile data are value-weighted returns of individual equities in size-sorted portfolios, with Decile 1 containing the smallest firms. Summary statistics for the international decile returns appear in Table 2.2 and are described in Section 2 above. We estimate the international regression models as panel/time-series models one country at a time. Results appear in Tables 2.4 and 2.5.

For each of the northern hemisphere countries, the onset/recovery coefficient is consistently negative for all deciles, just as reported above for the US equity decile returns data. The magnitude is generally largest and most statistically significant for the smallest firm-size decile, and the magnitude tends to decline as firm size increases. These findings suggest that, for the northern hemisphere countries, returns tend to be below average as SAD onset occurs in the fall and above average as people recover from SAD in winter, leading to above average returns for those investors holding equities through the winter. Turning to Australia, we see a strong, statistically significant SAD effect only for the smallest firm deciles; larger firm deciles show no statistical significance or even have a positive (generally insignificant) coefficient. For each country, an (untabulated) joint test of the SAD effect across deciles shows strong statistical significance, at the 0.2% level for Australia and better than 0.1% for the remaining countries, suggesting the SAD effect is significant overall for each country's equity market.

As reported above for the US, both Canada and Australia present mostly strong, statistically significant negative Monday effects, generally declining in magnitude as firm size increases. The Monday effect, however, is not evident in Germany, and in the UK we see a large, negative, statistically significant Monday effect only for mid-size firm deciles. In Canada and Germany, the tax-year effect is evident for smaller deciles but declines in magnitude and significance with firm size. For Australia and the UK, the tax-year effect is absent. The mixed findings across countries for the tax-year effect and the Monday effect are consistent with the findings of Kamstra et al. (2012), who report mixed evidence of these effects across dozens of international exchanges.

3.3 Evidence Based on Disaggregated Firm/Day-Level Equity Return Data

To supplement the decile-based analysis reported above, we also employed modern panel/time-series regressions using the full cross-section of firms rather than size-sorted portfolios. Using the full cross-section of firms in this context entails many millions of data points with cross-sections as large as several thousand firms over about 30 years of

Table 2.4 *Regression results for Canada and Germany based on size-sorted decile equity returns, January 1990–December 2019*

Panel A: Canada										
Decile → Statistic ↓	1	2	3	4	5	6	7	8	9	10
β_{OR}	−.25	−.19	−.21	−.19	−.18	−.18	−.14	−.17	−.14	−.08
Std. Err.	.055	.049	.048	.049	.050	.053	.052	.052	.049	.056
t-test	−4.6	−3.9	−4.4	−3.9	−3.7	−3.5	−2.7	−3.2	−2.9	−1.5
p-value	.000	.000	.000	.000	.000	.000	.004	.001	.002	.066
β_{Mon}	−.14	−.19	−.17	−.18	−.15	−.17	−.17	−.12	−.13	−.02
Std. Err.	.030	.030	.028	.028	.030	.031	.029	.030	.029	.031
t-test	−4.7	−6.1	−6.1	−6.3	−5.1	−5.5	−5.7	−4.0	−4.5	−.78
p-value	.000	.000	.000	.000	.000	.000	.000	.000	.000	.218
β_{Tax}	.148	.092	.105	.063	.100	.050	.017	.000	−.00	.003
Std. Err.	.040	.036	.035	.033	.036	.037	.036	.036	.035	.041
t-test	3.67	2.55	3.02	1.90	2.80	1.34	.455	.007	−.07	.067
p-value	.000	.005	.001	.029	.003	.091	.324	.497	.470	.473
R^2	.0084	.0097	.0101	.0093	.0076	.0072	.0062	.0041	.0046	.0004

Panel B: Germany

Decile → Statistic ↓	1	2	3	4	5	6	7	8	9	10
β_{OR}	−.31	−.20	−.29	−.17	−.19	−.19	−.18	−.16	−.17	−.15
Std. Err.	.076	.071	.063	.062	.064	.063	.068	.071	.068	.078
t-test	−4.1	−2.7	−4.5	−2.7	−3.0	−3.1	−2.6	−2.2	−2.6	−1.9
p-value	.000	.003	.000	.003	.001	.001	.004	.012	.005	.026
β_{Mon}	.050	.031	.049	.056	.033	.051	.044	−.01	.006	.031
Std. Err.	.041	.037	.035	.034	.036	.036	.038	.040	.037	.043
t-test	1.23	.817	1.40	1.62	.927	1.40	1.17	−.33	.154	.721
p-value	.110	.207	.081	.053	.177	.080	.121	.369	.439	.236
β_{Tax}	.278	.260	.230	.190	.157	.143	.164	.093	.035	−.01
Std. Err.	.061	.048	.053	.048	.049	.049	.048	.051	.047	.056
t-test	4.58	5.39	4.37	3.97	3.22	2.94	3.38	1.83	.740	−.24
p-value	.000	.000	.000	.000	.001	.002	.000	.034	.230	.407
R^2	.0060	.0051	.0072	.0043	.0033	.0032	.0031	.0014	.0012	.0007

Notes:

Results are based on estimating Equation (2.1) using Canadian and German value-weighted size-sorted decile return data for each country individually in a panel/time-series model.

β_{OR} is the coefficient estimate on the SAD onset/recovery variable developed by Kamstra et al. (2015); β_{Mon} is an indicator variable set to equal one if a trading day occurs on a Monday; β_{Tax} is an indicator variable set to equal one if a trading day occurs in the first month of the tax year (January).

We omit the intercept from the tabulated results for brevity. We calculate standard errors using MacKinnon and White's (1985) bootstrap heteroskedasticity-consistent method. Decile 1 is the smallest firm-size decile and Decile 10 the largest.

Table 2.5 Regression results for the UK and Australia based on size-sorted decile equity returns, January 1990–December 2019

Panel A: UK

Decile → Statistic ↓	1	2	3	4	5	6	7	8	9	10
β_{OR}	−.13	−.11	−.13	−.12	−.16	−.13	−.19	−.16	−.13	−.06
Std. Err.	.042	.042	.040	.040	.044	.047	.053	.055	.060	.064
t-test	−3.1	−2.7	−3.2	−2.9	−3.7	−2.8	−3.5	−3.0	−2.2	−.99
p-value	.001	.003	.001	.002	.000	.002	.000	.001	.015	.161
β_{Mon}	.053	.033	.001	−.03	−.08	−.07	−.09	−.09	−.08	.005
Std. Err.	.038	.021	.021	.021	.024	.026	.029	.030	.033	.034
t-test	1.40	1.59	.030	−1.2	−3.3	−2.7	−3.3	−3.0	−2.4	.147
p-value	.080	.056	.488	.108	.000	.003	.001	.002	.008	.442
β_{Tax}	.063	.087	.063	.059	.041	.030	.014	−.02	−.04	−.08
Std. Err.	.039	.026	.025	.026	.028	.032	.035	.038	.039	.043
t-test	1.60	3.36	2.58	2.25	1.47	.953	.395	−.54	−1.0	−1.8
p-value	.055	.000	.005	.012	.071	.170	.346	.294	.158	.033
R^2	.0003	.0030	.0026	.0023	.0041	.0025	.0035	.0026	.0017	.0005

Panel B: Australia

Decile → Statistic ↓	1	2	3	4	5	6	7	8	9	10
β_{OR}	−.16	−.04	−.10	−.02	.023	.084	.055	.052	.063	.094
Std. Err.	.048	.043	.044	.046	.049	.049	.050	.050	.049	.053
t-test	−3.3	−.89	−2.2	−.41	.480	1.73	1.10	1.05	1.27	1.77
p-value	.000	.187	.013	.341	.316	.042	.135	.148	.102	.038
β_{Mon}	−.09	−.10	−.08	−.06	−.08	−.07	−.07	−.04	−.04	.005
Std. Err.	.026	.024	.026	.025	.028	.029	.029	.029	.029	.030
t-test	−3.5	−4.1	−3.2	−2.4	−3.0	−2.6	−2.2	−1.5	−1.5	.155
p-value	.000	.000	.001	.008	.001	.005	.012	.071	.073	.439
β_{Tax}	.080	.009	.051	−.01	−.04	−.02	−.02	−.04	−.06	−.02
Std. Err.	.041	.034	.034	.035	.039	.041	.040	.041	.040	.043
t-test	1.93	.280	1.50	−.36	−.92	−.37	−.40	−.96	−1.5	−.50
p-value	.027	.390	.067	.361	.178	.357	.345	.168	.065	.307
R^2	.0037	.0026	.0026	.0009	.0015	.0014	.0009	.0006	.0008	.0004

Notes:
Results are based on estimating Equation (2.1) using UK and Australian value-weighted size-sorted decile return data for each country individually in a panel/time-series model.

β_{OR} is the coefficient estimate on the SAD onset/recovery variable developed by Kamstra et al. (2015), shifted by six months for Australia to account for its location in the southern hemisphere; β_{Mon} is an indicator variable set to equal one if a trading day occurs on a Monday; β_{Tax} is an indicator variable set to equal one if a trading day occurs in the first month of the tax year (April in the UK, July in Australia).

We omit the intercept from the tabulated results for brevity. We calculate standard errors using MacKinnon and White's (1985) bootstrap heteroskedasticity-consistent method. Decile 1 is the smallest firm-size decile, and Decile 10 the largest.

daily data. We estimate the SAD effect with disaggregated firm-level daily data, including fixed effects for both firm and year, and with controls for firm price, market capitalization, return volatility, and trading volume, all lagged one period. We conduct robust inference, making use of standard errors clustered by date and firm. The regression model we estimate for each country is as follows:

$$r_{i,t} = \alpha_{i,\text{Year}} + \beta_{\text{Mon}} \cdot \text{Mon}_t + \beta_{\text{Tax}} \cdot \text{Tax}_t + \sum_{\text{k}=1}^{3} \beta_{k,\text{OR}} \cdot \text{D}_{i,k,t-1} \cdot \text{OR}_t$$

$$+ \beta_{\text{ME}} \cdot \text{ME}_{i,t-1} + \beta_{\text{Vol}} \cdot \text{Vol}_{i,t-1} + \beta_{\text{Volat}} \cdot \text{Volat}_{i,t-1} + \beta_{\text{P}} \cdot \text{P}_{i,t-1} + \epsilon_{i,t}. \quad (2.3)$$

Here $r_{i,t}$ is the time-series of returns for firm i; Mon_t and Tax_t are defined as stated above to capture the Monday and tax-year effects; and $\text{D}_{i,k,t-1}$ are indicator variables to capture the market capitalization tercile of a firm i at time $t-1$. ($D_{i,k,t-1}$ equals 1 if firm i is in the k^{th} firm market capitalization tercile at time $t-1$ and 0 otherwise, with Tercile 1 corresponding to the smallest firms.) By interacting the market capitalization tercile dummy variable with the SAD onset recovery variable, OR_t, we allow the SAD effect to vary across firms in different firm-size terciles. $\text{ME}_{i,t-1}$ is firm i's market capitalization at time $t-1$ and $\text{Vol}_{i,t-1}$ is firm i's share trading volume at time $t-1$ (in thousands). $\text{Volat}_{i,t-1}$ is firm i's return volatility at time $t-1$, calculated using daily high/low prices: Volatility = 200*(High−Low)/(High+Low). $\text{P}_{i,t-1}$ is firm i's firm price in USD at time $t-1$. The intercept captures firm and year fixed effects.

Tables 2.6–2.8 contain results for the US, Canada, Germany, the UK, and Australia. Column (1) in each country's set of results presents the simplest model, including only the SAD onset/recovery variables. Column (2) contains results based on the model most comparable to the decile regressions considered above (although here the Monday and tax-year effects are constrained to be equal across all firms, unlike the case with the decile model, which allows variation in these effects across deciles). Column (3) contains results for the most parameterized model, including many additional controls. All of these regressions include fixed effects for year and firm, and we calculate clustered standard errors for each model, clustered by date and firm.

In each of the tables we see the SAD effect is statistically significant and strongest for the smallest size tercile (with the exception of the UK, for which estimates are similar across terciles). The SAD effect is smallest in magnitude and significance for the US and Australia, the two countries closest to the equator. The effect is larger and more significant for the three most northerly countries (Canada, Germany, and the UK), even for the most heavily parameterized specification. The SAD effect coefficient magnitudes roughly match those reported above for the decile data.

For the US, the Monday effect is weaker than we see in the decile regressions, and the tax-year effect disappears completely. This is likely a result of the restriction that the coefficient value be the same for all firms, and the fact that we are estimating the model over a period for which the Monday and tax-year effects were waning (1990–2019). For Australia, the Monday effect is strongly significant, in contrast to the decile regressions. Canada's tax-year and Monday effect coefficients are roughly equivalent to averages of those coefficients from the decile regressions. Germany continues to exhibit very strong tax-year effects and no Monday effect, and the UK exhibits stronger tax-year and Monday effects than with the decile regressions.

Table 2.6 Regression results for the US with firm-level data, January 1990–December 2019

	(1)	(2)	(3)
$\beta_{1,OR}$	−0.080**	−0.077**	−0.076*
	(0.039)	(0.039)	(0.041)
$\beta_{2,OR}$	−0.074	−0.071	−0.079
	(0.060)	(0.060)	(0.060)
$\beta_{3,OR}$	−0.090	−0.087	−0.093
	(0.062)	(0.062)	(0.062)
β_{Mon}		−0.104***	−0.103***
		(0.029)	(0.030)
β_{Tax}		0.036	0.023
		(0.037)	(0.038)
β_{ME}			−0.0004**
			(0.0002)
β_{Vol}			0.021***
			(0.003)
β_{Volat}			2.537***
			(0.554)
β_{P}			−0.002***
			(0.0002)
Firm & Year Fixed Effects	Y	Y	Y
N	41,416,936	41,416,936	38,873,910
R^2	0.002	0.002	0.002
Adjusted R^2	0.002	0.002	0.002

Notes:
Results are based on estimating Equation (2.3) using US disaggregated firm-level daily data in panel/time-series models.

$\beta_{1,OR}$, $\beta_{2,OR}$, and $\beta_{3,OR}$ are estimates that capture the SAD effect for the smallest through largest terciles of firms, respectively, based on interacting tercile indicator variables with the SAD onset/recovery variable developed by Kamstra et al. (2015).

β_{Mon} is the coefficient estimate on an indicator variable set to equal one if a trading day occurs on a Monday, and β_{Tax} is the coefficient estimate on an indicator variable set to equal one if a trading day occurs in the first month of the US tax year. β_{ME} is the coefficient estimate on firm market capitalization, and β_{Vol} is the coefficient estimate on firm share trading volume. β_{Volat} is the coefficient estimate on firm return volatility calculated using daily high/low prices: $\text{Volatility} = 200\,(\text{High} - \text{Low})/(\text{High} + \text{Low})$. β_{P} is the coefficient estimate on firm share price.

The regressions include fixed effects for year and firm, and we calculated clustered standard errors for each model, clustered by date and firm.

*, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

Altogether, the results based on the individual firm-level data broadly confirm the findings from the decile regressions. There is a robust SAD effect in the equity markets, strongest in far northerly latitudes and in smaller firms; and there is inconsistent but intriguing evidence of tax-year and Monday effects across countries. The longer time-series of US data, which permits long windows for rolling-window analysis, suggests that some of the variability in the Monday and tax-year effects across countries might arise from the relatively shorter samples in countries other than the US. These two effects appear to be

Table 2.7 Regression results for Canada and Germany with firm-level data, January 1990–December 2019

	Canada			Germany		
	(1)	(2)	(3)	(1)	(2)	(3)
$\beta_{1,OR}$	−0.221***	−0.221***	−0.214***	−0.201***	−0.180***	−0.133*
	(0.046)	(0.046)	(0.052)	(0.066)	(0.066)	(0.072)
$\beta_{2,OR}$	−0.182***	−0.183***	−0.173***	−0.182**	−0.161**	−0.136*
	(0.051)	(0.051)	(0.054)	(0.075)	(0.075)	(0.078)
$\beta_{3,OR}$	−0.125**	−0.125**	−0.123**	−0.150*	−0.130	−0.102
	(0.052)	(0.052)	(0.053)	(0.082)	(0.082)	(0.083)
β_{Mon}		−0.149***	−0.156***		0.024	0.025
		(0.027)	(0.029)		(0.039)	(0.041)
β_{Tax}		0.067**	0.075**		0.213***	0.216***
		(0.032)	(0.035)		(0.052)	(0.056)
β_{ME}			−0.002**			−0.003***
			(0.001)			(0.001)
β_{Vol}			0.071***			0.061***
			(0.003)			(0.004)
β_{Volat}			0.009**			−0.0003
			(0.004)			(0.005)
β_P			0.001***			0.001***
			(0.0002)			(0.0002)
Firm & Year Fixed Effects	Y	Y	Y	Y	Y	Y
N	5,582,327	5,582,327	4,855,390	4,400,776	4,400,776	4,002,602
R^2	0.002	0.002	0.003	0.003	0.003	0.004
Adjusted R^2	0.001	0.002	0.003	0.002	0.002	0.003

Notes:
Results are based on estimating Equation (2.3) using disaggregated firm-level daily data in panel/time-series models.

$\beta_{1,OR}$, $\beta_{2,OR}$, and $\beta_{3,OR}$ are estimates that capture the SAD effect for the smallest through largest terciles of firms, respectively, based on interacting tercile indicator variables with the SAD onset/recovery variable developed by Kamstra et al. (2015).

β_{Mon} is the coefficient estimate on an indicator variable set to equal one if a trading day occurs on a Monday, and β_{Tax} is the coefficient estimate on an indicator variable set to equal one if a trading day occurs in the first month of the tax year. β_{ME} is the coefficient estimate on firm market capitalization, and β_{Vol} is the coefficient estimate on firm share trading volume. β_{Volat} is the coefficient estimate on firm return volatility calculated using daily high/low prices: Volatility = 200 (High − Low) / (High + Low). β_P is the coefficient estimate on firm share price.

The regressions include fixed effects for year and firm, and we calculated clustered standard errors for each model, clustered by date and firm.

*, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

waning in the US over the last 40 years (see Figure 2.2), and perhaps also around the world. Furthermore, because these two effects are strongest for small firms (which are more prevalent in non-US equity markets), the variability in tax-year and Monday coefficients across countries may simply reflect differences in typical firm sizes across countries. As to why the tax-year and Monday effects are waning, we can only speculate that

Table 2.8 Regression results for the UK and Australia with firm-level data, January 1990–December 2019

	UK			Australia		
	(1)	(2)	(3)	(1)	(2)	(3)
$\beta_{1,OR}$	−0.149***	−0.117***	−0.102**	−0.079**	−0.074*	−0.079*
	(0.035)	(0.037)	(0.040)	(0.039)	(0.039)	(0.045)
$\beta_{2,OR}$	−0.164***	−0.132***	−0.129***	0.033	0.038	0.037
	(0.040)	(0.041)	(0.044)	(0.046)	(0.046)	(0.048)
$\beta_{3,OR}$	−0.142**	−0.110*	−0.106*	0.056	0.061	0.064
	(0.055)	(0.057)	(0.057)	(0.050)	(0.050)	(0.050)
β_{Mon}		−0.039*	−0.046**		−0.059**	−0.061**
		(0.022)	(0.023)		(0.024)	(0.026)
β_{Tax}		0.087***	0.088***		0.074***	0.075**
		(0.030)	(0.032)		(0.028)	(0.029)
β_{ME}			−0.002***			−0.001
			(0.001)			(0.001)
β_{Vol}			0.062***			0.045***
			(0.004)			(0.003)
β_{Volat}			0.017***			0.008
			(0.004)			(0.006)
β_{P}			0.004***			0.001
			(0.001)			(0.0005)
Firm & Year Fixed Effects	Y	Y	Y	Y	Y	Y
N	5,015,967	5,015,967	4,490,366	2,107,727	2,107,727	1,897,210
R^2	0.002	0.002	0.002	0.003	0.003	0.003
Adjusted R^2	0.001	0.001	0.002	0.002	0.002	0.003

Notes:
Results are based on estimating Equation (2.3) using disaggregated firm-level daily data in panel/time-series models.

$\beta_{1,OR}$, $\beta_{2,OR}$, and $\beta_{3,OR}$ are estimates that capture the SAD effect for the smallest through largest terciles of firms, respectively, based on interacting tercile indicator variables with the SAD onset/recovery variable developed by Kamstra et al. (2015), shifted by six months for Australia.

β_{Mon} is the coefficient estimate on an indicator variable set to equal one if a trading day occurs on a Monday, and β_{Tax} is the coefficient estimate on an indicator variable set to equal one if a trading day occurs in the first month of the tax year. β_{ME} is the coefficient estimate on firm market capitalization, and β_{Vol} is the coefficient estimate on firm share trading volume. β_{Volat} is the coefficient estimate on firm return volatility calculated using daily high/low prices: Volatility = 200 (High − Low) / (High + Low). β_P is the coefficient estimate on firm share price.

The regressions include fixed effects for year and firm, and we calculated clustered standard errors for each model, clustered by date and firm.

*, **, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

it may be an anomaly that is becoming cheaper to arbitrage over time as market liquidity and sophistication increase. Sudden awareness of these anomalies (say, with publication in journals) and subsequent efforts to arbitrage them undoubtedly figure into this phenomenon (see, for instance, McLean and Pontiff, 2016).

4 USING GOOGLE SEARCH VOLUME INDEX DATA TO MEASURE SAD

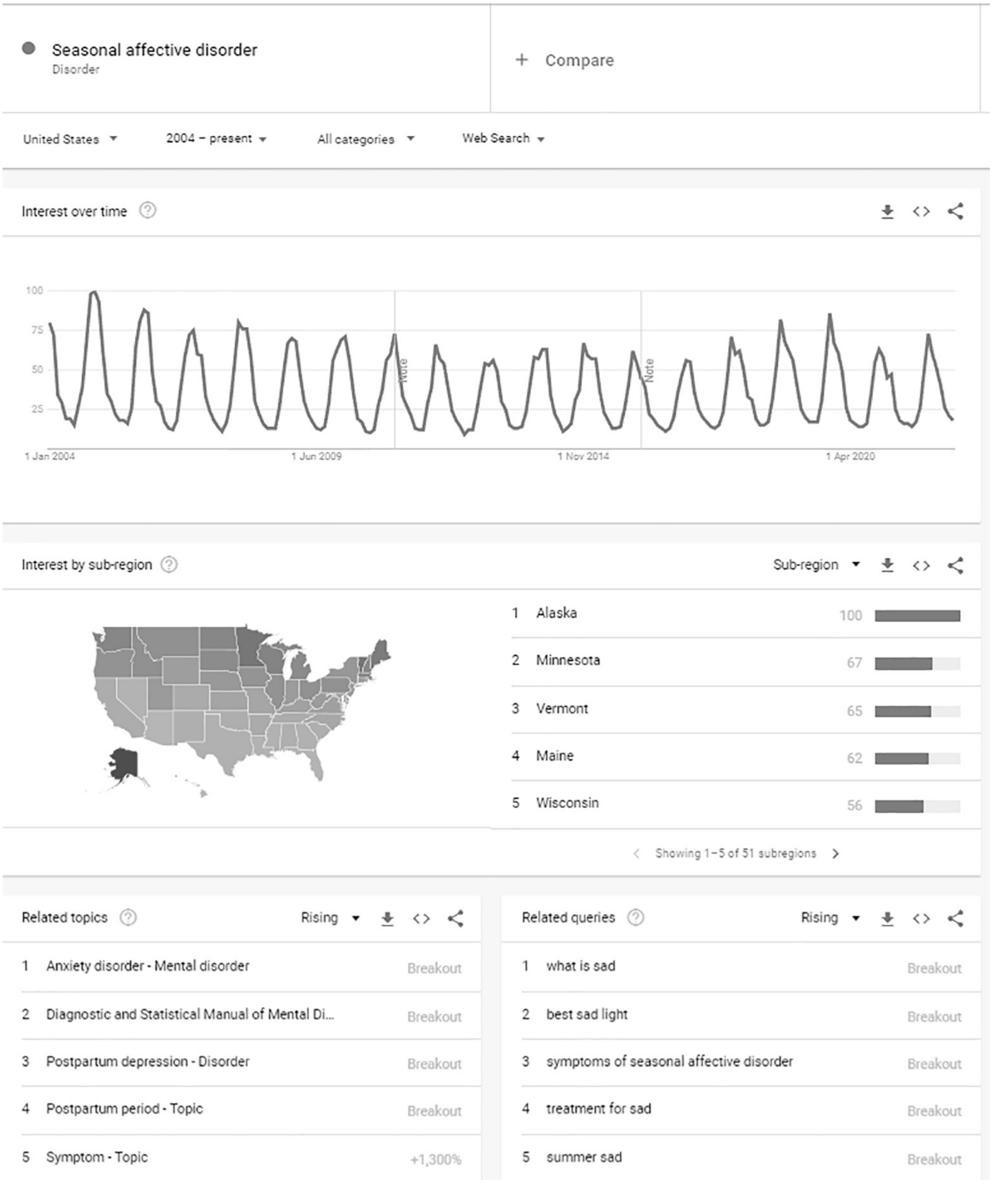
The use of Google Search Volume Index (SVI) data, also known as Google Trends, has become prevalent in behavioral finance research, often to identify retail investor attention (e.g., Da et al., 2011). SVI data have also been used to identify a range of aspects of people's current situations in a given location, including employment status, interest in purchasing real estate, cinema attendance, and health status.[6]

Given the utility of SVI data to identify otherwise difficult-to-assess time-varying characteristics of people by location, we anticipate they may be useful in proxying for seasonal depression, which varies by latitude and hemisphere. To form a new proxy for the prevalence of SAD in a given country over time, we collect data by country on Google searches related to "seasonal affective disorder," selecting the subcategory "disorder" for greater specificity. For each country, we collect search volume data monthly back to the earliest availability (January 2004)—except for Australia, for which we go back to January 2007 due to sparsity of the Australian search data prior to that point. The SVI data potentially reflect the *incidence*, or prevalence, of SAD at a local country level. To create a proxy analogous to the SAD onset/recovery variable, which reflects *changes* in SAD incidence, we calculate the change in search volume and normalize the resulting series to match the scale of the SAD onset/recovery variable.[7] The resulting SVI proxy for onset/recovery is highly correlated with our primary onset/recovery variable, with roughly 80–90% correlation for countries other than Australia and around 60% for Australia.

Figure 2.3 displays the results of a Google Trends search for "seasonal affective disorder" (with the "disorder" subcategory selected, as shown in the top-left corner of the figure). The region is set to the US, the time range is between January 2004 and May 2022, and the search content is "Web Search." We see a distinct annual seasonal pattern associated with the onset of and recovery from SAD similar to the seasonality we observe in data from the clinical studies Kamstra et al. (2015) used to construct the SAD incidence and SAD onset/recovery variables. The Google SVI output shown in Figure 2.3 also provides cross-sectional detail across US states in the map, showing much greater volume of searches in higher-latitude states, greatest in Alaska and lowest in southern states. Reassuringly, items appearing under "Related topics" are all health-focused (while some items do not pertain directly to SAD, the fact that they are all health-related confirms we are not picking up random searches), and items appearing under "Related queries" are all clearly linked to SAD.

Our stock and government bond return samples begin before Google SVI search figures were available. For those pre-2004 dates for which SVI data are unavailable (pre-2007 for Australia), we replace missing SVI values with the average monthly or daily SVI values in the sample for 2004 and later (2007 and later for Australia). The average monthly SVI values we use for each country's pre-2004 (or pre-2007) values appear in Panel A of Figure 2.1 (depicted by dotted lines), and each country's SVI time-series for 2004 (or 2007) and later appears in Panels B–F.

We re-estimate our decile stock return and Treasury return regression models, Equations (2.1) and (2.2), replacing the SAD onset/recovery variable derived from patients' clinical symptoms with a country-specific Google SVI estimate of SAD onset/recovery. Table 2.9 contains results pertaining to the coefficient estimates for the SVI onset/recovery proxy.



Notes:
The graph labeled "Interest over time" depicts search volume.
The map labeled "Interest by sub-region" depicts search intensity by state, with darker shading corresponding to more intense search activity.
The bottom panels list related topics and queries.

Figure 2.3 Google Trends search result for the US for "seasonal affective disorder" and "disorder" subcategory, January 2004–May 2022

Table 2.9 Regression results using country-specific Google SVI onset/recovery proxies

Panel A: US Government Bond Returns

Maturity → Statistic ↓	30yr	20yr	10yr	7yr	5yr	2yr
$\beta_{OR:SVI}$	1.61	1.27	1.10	.954	.793	.395
t-test	2.47	2.20	2.54	2.58	2.61	2.24
p-value	.007	.014	.005	.005	.005	.012

Panel B: Equity Returns

Decile → Country & Statistic ↓	1	2	3	4	5	6	7	8	9	10
US										
$\beta_{OR:SVI}$	−.12	−.11	−.10	−.08	−.08	−.08	−.09	−.07	−.06	−.04
t-test	−2.9	−2.5	−2.4	−2.1	−2.1	−2.1	−2.3	−1.7	−1.7	−1.2
p-value	.002	.006	.008	.017	.017	.017	.012	.041	.042	.117
Canada										
$\beta_{OR:SVI}$	−.42	−.33	−.36	−.33	−.31	−.31	−.25	−.26	−.22	−.12
t-test	−6.3	−5.6	−6.1	−5.6	−5.2	−4.8	−4.0	−4.1	−3.8	−1.8
p-value	.000	.000	.000	.000	.000	.000	.000	.000	.000	.034
Germany										
$\beta_{OR:SVI}$	−.37	−.24	−.30	−.24	−.24	−.26	−.23	−.22	−.21	−.20
t-test	−4.2	−2.9	−4.2	−3.4	−3.3	−3.6	−3.1	−2.8	−2.8	−2.2
p-value	.000	.002	.000	.000	.001	.000	.001	.002	.002	.013
UK										
$\beta_{OR:SVI}$	−.32	−.14	−.20	−.19	−.23	−.17	−.24	−.21	−.18	−.10
t-test	−3.1	−3.1	−4.2	−4.0	−4.5	−3.3	−4.0	−3.2	−2.6	−1.3
p-value	.001	.001	.000	.000	.000	.001	.000	.001	.004	.093
Australia										
$\beta_{OR:SVI}$	−.24	−.11	−.11	−.07	−.05	.054	.043	.007	.010	.059
t-test	−4.3	−2.0	−2.1	−1.2	−.84	.842	.678	.117	.157	.901
p-value	.000	.021	.016	.122	.201	.200	.249	.454	.437	.184

Notes:
Panel A: Results are based on estimating Equation (2.2) using US government bond return data in a panel/time-series model for January 1972–December 2019. $\beta_{OR:SVI}$ is the coefficient estimate on the SAD onset/recovery proxy based on Google SVI data. The intercept is omitted for brevity.

Panel B: Results are based on estimating Equation (2.1) on a country-by-country basis using value-weighted size-sorted decile return data in a panel/time-series model (sample period January 1926–December 2019 for the US and January 1990–December 2019 for other countries). As in Panel A, $\beta_{OR:SVI}$ is the coefficient estimate on the SAD onset/recovery proxy based on Google SVI data. Regression models include a Monday indicator set to equal one if a trading day occurs on a Monday and tax-year indicator variable set to equal one if a trading day occurs in the first month of the tax year. Intercept, Monday, and tax-year coefficient estimates are omitted for brevity. Decile 1 is the smallest firm-size decile, and Decile 10 the largest.

In all cases, we calculate standard errors using MacKinnon and White's (1985) bootstrap heteroskedasticity-consistent method.

Recall that the SVI proxy for SAD onset/recovery is scaled to match the magnitude of Kamstra et al.'s (2015) SAD onset/recovery variable, facilitating the comparison of results based on the two different onset/recovery measures. For US Treasuries, appearing in Panel A of Table 2.9, there is very little change in results using the Google SVI onset/recovery proxy relative to Kamstra et al.'s onset/recovery measure; in Panel A we see slightly stronger results for the longest-term securities. The regression results using the Google SVI onset/recovery proxy for equity returns appear in Panel B. For the US size-sorted equities, relative to results considered above using the Kamstra et al. (2015) clinical onset/recovery measure, we now see a slightly stronger SAD effect in the small-firm deciles and little change in the large-firm deciles. The Google SVI onset/recovery measure is strongly positively correlated with the clinical measure, with a correlation coefficient of 0.87, so perhaps the similarity of results is unsurprising. In the international data, we see uniformly stronger results using the country-specific Google SVI measure of SAD onset/recovery. As before, the SAD effect is strongest for the smallest firms, declining in magnitude and significance as the size decile increases. Australia remains the weakest set of results (not unexpected because its population resides closest to the equator); but now all five of the smallest firm deciles present with negative coefficients, and the three smallest firm deciles show strong SAD effects—very strong for the smallest firm decile, with a t-test statistic value exceeding 4. The largest t-test statistics for US equities are close to 3 in magnitude, over 6 for Canada, and over 4 for Germany and the UK.

We also re-estimate the regression model based on firm-level data, Equation (2.3), replacing the clinical onset/recovery variable with the Google SVI-derived measure. Results for the coefficient estimates on the Google proxy for onset/recovery are shown in Table 2.10. We see that the magnitude of the SAD effect based on use of the SVI data is similar in magnitude, and perhaps even a bit larger for each country, than seen in Tables 2.6–2.8. Overall, the SAD effect is evident in all of the countries, strongest and uniformly significant for the smallest third of the firms and generally declining with increasing firm size.

5 CONCLUDING REMARKS

A major feature of people's natural environments is daylight. The changing balance between daylight and darkness through the seasons has consequences for the mood and risk preferences of market participants as they make financial decisions at different points of the year, which in turn has implications for financial markets. In examining US Treasury returns and equity returns for the US, Canada, the UK, Germany, and Australia, we found large, statistically significant seasonal variation in returns consistent with market participants experiencing seasonal variation in daylight, mood, and risk aversion. We showed these effects in size-sorted stock return deciles and in individual firm-level data for all the countries in our sample. We also introduced a novel measure of seasonally varying investor risk aversion based on country-specific Google Trends data.

While the seasonal affects we document vary by location, they are distinct from the influence of geography on financial decision making (summarized by Wang in Chapter 6 of this volume), which may arise for reasons such as ease of information acquisition, familiarity, and culture, as opposed to daylight exposure. The connections between

Table 2.10 Regression results using firm-level data and country-specific Google SVI onset/recovery proxies, January 1990–December 2019

Country → Statistic ↓	USA	Canada	Germany	UK	Australia
$\beta_{1,OR:SVI}$	−0.100**	−0.356***	−0.213***	−0.225***	−0.095*
	(0.044)	(0.062)	(0.079)	(0.047)	(0.056)
$\beta_{2,OR:SVI}$	−0.083	−0.294***	−0.191**	−0.195***	0.031
	(0.062)	(0.064)	(0.083)	(0.045)	(0.064)
$\beta_{3,OR:SVI}$	−0.079	−0.177***	−0.084	−0.133**	0.060
	(0.063)	(0.064)	(0.087)	(0.059)	(0.064)

Notes:
Results are based on estimating Equation (2.3) using disaggregated firm-level daily data in a panel/time-series model, one country at a time.

$\beta_{1,OR:SVI}$, $\beta_{2,OR:SVI}$, and $\beta_{3,OR:SVI}$ are estimates that capture the SAD effect for the smallest through largest terciles of firms, respectively, based on interacting tercile indicator variables with the Google SVI proxy for SAD onset/recovery. The model includes controls for the Monday effect, tax effect, firm market capitalization, firm share trading volume, firm return volatility, and firm share price, with coefficient estimates omitted from the table for brevity.

The regressions include fixed effects for year and firm, and we calculated clustered standard errors for each model, clustered by date and firm.

*, *, and *** indicate statistical significance at the 10, 5, and 1% levels, respectively.

daylight and seasonal variation in mood and risk preferences are believed to arise in part via seasonal changes in neurotransmitters such as serotonin and dopamine (Sohn and Lam, 2005). For a broader discussion of neurofinance, including the role of neurotransmitters in financial decision making more generally, see Chapter 4 in this volume by Payzan-LeNestour.

Overall, the seasonal connections between daylight, mood, risk preferences, and international financial market returns highlight the role of human nature in financial decisions at the micro level and aggregate market outcomes at the macro level.

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NOTES

1. We thank Ken French for making this valuable resource freely available.
2. A lack of return data for international government bonds constrains us to investigate only US government bond data.
3. We apply the following filters on the international equity returns data. We exclude obvious data errors (e.g., price > daily high price, price < daily low price); missing lagged, high, or low price;

missing daily volume or zero daily volume; and data for which the returns swing wildly (e.g., −80% followed by +400%). We exclude stale price data, for which the last observation was more than seven days prior, and we exclude observations if the price on the previous day was below US$1.

4. The SAD onset/recovery variable is available from www.LisaKramer.com/data.html. The variable is based on the clinical timing of the onset of and recovery from SAD symptoms among patients who experience SAD. For further details, see Kamstra et al. (2015).
5. When comparing coefficient estimate magnitudes for equities versus Treasuries, keep in mind that the equity returns are daily and the Treasury returns are monthly.
6. See Hand and Judge (2012), Dietzel et al. (2014), González-Fernández and González-Velasco (2018), and Hsiang et al. (2018).
7. Due to noise in the data (Google provides only a random sample of search data) we smooth the search data using a three-month centered moving average, in addition to normalizing the scale. Because the Google SVI data we download are monthly, we interpolate the daily values.

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