2010

Further Examination of Equity Returns and Seasonal Depression

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ABSTRACT

Seasonal Affective Disorder (SAD) induces investors to shift resources away from risky investments (such as equity) and towards safer alternatives (such as fixed income) during the Fall, while stimulating the opposite action in the Winter. Existing studies, however, fail to account for the possibility that SAD could further motivate investors to shift exposure among different subsets of equity, rather than simply across broad asset categories. We explore this possibility by examining the impact of SAD on the returns of "safe" and "risky" equity sectors (i.e., industries), as well as on equity at different levels of market capitalization. We find the SAD effect to be generally prevalent throughout all equity sectors, regardless of historical or perceived risk level, implying that there is no incremental sector reallocation. We do, however, find that SAD has a more significant impact on smaller capitalization stocks, suggesting that investors view large capitalization stocks as relatively safe investments.

INTRODUCTION

A principal area of financial research involves identifying potential drivers of stock market returns. If discovered, one can then attempt to capitalize on this information by investing accordingly. Historically, most prospective determinants that have been examined are fundamental in nature and are, thus, attributable to an information-based influence. However, over the past decade a number of researchers have turned to non-fundamental, or behavioral, explanations for market behavior. With this increased focus on behavioral finance, researchers have added significantly to the way we view financial markets.

One such example comes from Kamstra, Kramer, and Levi (2003) (henceforth KKL), who examine a purely behavioral influence on stock market returns, both in the United States and worldwide. Specifically, they examine the impact of Seasonal Affective Disorder (SAD), which is an extensively documented psychological condition that is known to cause increased pessimism (and, in extreme cases, depression) during the Fall and Winter months. Using a proxy of SAD that measures the amount of daylight for each day of the year, they find an asymmetric effect on stock market returns around the Winter Solstice, the day which marks increasing daylight hours in the immediate future.

Returns are lower, on average, on days leading up to the Solstice, as the amount of daylight declines; however, this pattern reverses following the Solstice as days begin to 'lengthen.' The underlying rationale for this asymmetric pattern is likely based on a risk-reward shift. More specifically, the natural forces of supply and demand, alongside the historically proven relationship between risk and return, suggest the explanation that investors are prone to reduce or eliminate risky positions (such as equity) and replace them with safer alternatives during the Fall, while taking the opposite approach in the Winter.

Perhaps just as interesting an issue, however, concerns how this reallocation of resources actually takes place to accomplish the end result of "safer" portfolios for those investors who are rendered more pessimistic by SAD. For example, Kamstra, Kramer, and Levi (2008) find support for the notion that investors generally reallocate across broad asset classes by moving out of equity (i.e., higher risk) assets

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and into debt (i.e., lower risk) investments. Specifically, they identify an asymmetric effect in the U.S. Treasury market that is opposite that found in the equity market.

It is also possible, however, that investors could reallocate within the broad equity sector to further reduce the amount of risk to which they are exposed. This movement would not necessarily be captured in prior studies since a shift away from one equity category could be offset by the movement to another equity category. Thus, we fill this gap by examining whether SAD further impacts equity markets through sector-based migration, i.e., a shifting of resources *within* class rather than only *between* classes.

Specifically, we consider two potential migration patterns. First, we examine, via the Fama-French 48 Industry portfolios, the returns on equity sectors (e.g., Agriculture, Drugs, Autos, Retail, etc.) for the time period 1963 to 2007. We find the SAD effect is persistent across almost every industry, even when segmented by perceived or historically determined levels of risk. Thus, it does not appear that investors generally replace one equity sector with another.

Second, we also segment the market by size and find that all but the very largest of securities (i.e., the top quintile) experience a consistent SAD effect. The influence is insignificant in the largest capitalization sample, perhaps due to the relative safety of this group. Thus, the desire to shift resources as the symptoms associated with SAD increase (and subsequently decrease) is muted. However, it may also be consistent with the understanding that large-cap equities are less susceptible to seasonal effects than their small-cap counterparts.[1]

In sum, we find little support for the hypothesis that investors shift among industries (i.e., sector migration) and conclude that, if such a seasonally-induced shift is indeed occurring, it is only among broad asset classes (i.e., equity to debt) and not among equity sectors (i.e., equity to equity). Further, our size findings indicate that the broad asset reorganization that does occur is driven by liquidation of the smallest capitalization equities, as the largest capitalization stocks are minimally impacted by SAD.

The remainder of the paper proceeds as follows: Section II provides background information; Section III introduces data and methods; Section IV presents results; and Section V concludes.

BACKGROUND

Kamstra, Kramer, and Levi (2003) provide the seminal work in examining the link between seasonal depression and equity market returns worldwide. The chain of causality is straightforward. First, a significant number of investors are likely influenced by SAD due to its prevalence among individuals.[2] Second, those afflicted will experience an increase in the symptoms associated with SAD as the number of hours of daylight decrease throughout the Fall months.[3] Third, the increased prevalence of the symptoms will likely result in alternative investing behavior by those afflicted.[4] Fourth, this collective adjustment (from risky to safer investments) is powerful enough to affect the entire market. KKL find strong evidence in support of this latter notion, not only in the US, but in several markets worldwide.[5]

It has also been documented that other, more specific, aspects of financial markets are influenced by seasonal depression. For example, Dolvin and Pyles (2007) find an increase in the level of underpricing and offer price revisions in Initial Public Offerings (IPOs) that went public during SAD periods relative to the rest of the year. These findings suggest more uncertainty surrounding SAD issues relative to non-SAD issues, a finding that is consistent with an increase in the general level of market pessimism. Further, Dolvin, Pyles, and Wu (2009) suggest the influence of SAD is not restricted to "naïve" retail investors. They examine the level of analysts' earnings estimates in SAD periods relative to non-SAD periods and find the amount of pessimism embedded in earnings forecasts is significantly higher during SAD periods, which suggests that financial professionals themselves may be affected by the disorder.

It should be noted that the influence of SAD on financial markets is certainly not without debate. For example, Jacobsen and Marquering (2008) suggest that documented SAD effects may be spurious and that conclusions drawn from them should be tempered. Also, a line of literature has developed that casts doubt on the chain of causation developed by KKL. For example, Parker and Tavasolli (2000) find that people in negative moods are *less* likely to become risk averse. Further, they find lack of sunlight may actually increase the desire to accept risk. Thus, the debate over whether the seasonal patterns documented are caused by SAD is still ongoing. However, there is no question that the pattern exists and that SAD is certainly one possible explanation.

DATA AND METHODS

We begin by identifying a proxy for seasonal depression. Following KKL, we create *SAD*, which is a modified binary variable, defined as:

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

where H_t is the amount of time between sunset and sunrise on day *t*. We deduct 12 (the average number of night hours over the entire year) to obtain a measure (i.e., $H_t - 12$) that reflects the length of night relative to an average day.[6] The specification also addresses the medical evidence that suggests SAD only occurs during Fall and Winter months.[7]

Since we examine stock exchanges in the United States, which lies in the Northern Hemisphere, we designate the beginning of Fall as September 21 and the beginning of Winter as December 21. Thus, SAD takes on non-zero positive values for the days between September 21 and March 20 of each year, and is zero for the remainder. This is consistent with evidence suggesting SAD is only prevalent during half of the year. Also following KKL, we create the dummy variable *Fall* to examine the asymmetric effect across the Fall and Winter periods. *Fall* equals one if the observation is during the September 21 to December 20 period, zero otherwise.

To explore market returns, we collect two series of data from Kenneth French's website. First, we gather the Fama-French 48 industry portfolio returns (see Fama and French (1997) for an example of the classic use). All NYSE, AMEX, and NASDAQ firms are assigned an industry at the end of June each year. The return of each basket of securities (i.e., each industry) is then calculated for each day of the upcoming year. These portfolios provide an ideal vehicle for testing our hypothesis, as the values are available daily from 1963 to present. Our sample period ends in 2007, thus we have 44 years of daily observations to examine.

An important issue in a study such as this is the perception of risk. Since the hypothesis of a market shift due to SAD is predicated on the ability of investors to identify risky and safe investments (or industries), the question of how to accurately measure this risk is an important one. We choose to examine this segmentation using two distinct definitions. The first is entirely subjective and based upon the authors' preconceived notions and casual examination of the investing landscape. In other words, we simply segment the industries into "risky" and "safe" categories based upon how we believe most investors perceive them. While this may seem haphazard, it can certainly be argued that this is the way many (if not most) investors view the investment world. Rather than conducting an in-depth examination of historical risk-return dynamics, it is likely they instead invest according to what they think to be the case.

However, it is also possible that there is a more quantifiable segmentation at play by those who may wish to shift risk. In fact, if SAD-afflicted investors are indeed experiencing increased pessimism and do not wish to take risk, it is possible they would be a prime example of a subgroup that would put forth the extra effort to measure risk levels instead of assume them. Thus, we also classify risk categories by calculating the average three-year rolling standard deviation for each industry, subsequently labeling those industries with average volatility below the median as "safe" and those above as "risky."[8]

Table 1 presents average daily returns and three-year rolling standard deviations for each of the 48 industries, along with the results of the two segmentation strategies for each. Interestingly, the subjective and quantitative methods result in the same classification for only approximately half of the industries. This could be an important point as it suggests the possibility that investors may *try* to shift risk among industries without having an accurate understanding of which are indeed riskier.

Also included in Table 1 are combinations of the risky and safe categories. *SSafe* and *SRisky* are the averages for the safe and risky industries, respectively, as segmented by our subjective approach. *QSafe* and *QRisky* represent the same when segmenting by average historical volatility. One would expect the risky portfolios to have higher average returns and standard deviations under both segmentations. However, while the quantitative segmentation naturally results in the predicted relationship, the subjective approach does not. This is again possible evidence of our failure to accurately define risk when done subjectively, a problem that is likely to be replicated by the average investor.

We further examine the data by segmenting observations into SAD (i.e., Fall and Winter) and non-SAD (i.e., Spring and Summer) periods and test for differences in average values between the two periods. Results are presented in Table 2. While this is not an exact examination since *SAD* is not a strict binary variable, it provides a helpful approximation. Interestingly, all but two of the industries experience higher average returns during the SAD period. Of these, the difference is significant (at the 10% level or better) in 35 of the 47. This is consistent with the findings of Kamstra, Kramer, and Levi (2003) and suggests that returns from certain industries do not experience different patterns based upon risk level. In fact, both the combined risky and safe portfolios (for both the subjective and quantitative approach), indicate a highly significant difference between average daily returns in the two periods. The only exceptions are Gold and Oil, which one might expect to do well if investors do undertake a “flight” to safety.

In addition, we also examine only the SAD sample (i.e., Fall and Winter days) segmented by each season since the asymmetric effect around the Winter solstice is a primary conclusion from KKL. We find results that are entirely consistent with those predicted by KKL. Specifically, we find that 45 of the 48 industries experience higher levels of returns during the Winter (following the solstice) than during the Fall (prior to the solstice). Of these, 29 differences are significant. Further, two of the three industries (Food and Utilities) that go against this norm are among the safest in the sample and only the Utilities industry has a marginally significant difference. The combined safe and risky portfolios also support the findings of KKL as the levels of returns are significantly higher in the Winter than Fall in all four classifications. It is worthy of note, however, that the differences in the two risky classifications are higher than those in the corresponding safe classifications.

Our second primary area of analysis involves collecting daily market returns on indices of securities segmented by size. Specifically, we examine quintile portfolios of the market (all NYSE, AMEX, and NASDAQ firms with available data) as determined by capitalization (measured at the end of each June).[9] With these data, we are able to examine whether the effect of SAD is contingent (at least in part) on another well-known risk dynamic. Specifically, smaller stocks are typically known to be riskier, on average, primarily due to the lack of available information (relative to larger equities). The hypothesis suggested by the risk-reward shift as presented earlier is that the SAD effect should be more pronounced in smaller stocks as they have a greater degree of risk.

We again begin our analysis by examining the average returns during SAD and non-SAD periods, and we present these results in Table 3. We find a significantly higher level of average daily returns during SAD periods relative to non-SAD periods for each of the five size quintiles. However, the gap seems to narrow with increased size, as evidenced by a .060% difference for the smallest quintile compared to a .034% difference for the largest, as well as by a smaller *t*-statistic for this difference. We again examine only the SAD period, segmenting by season and find higher levels of returns during Winter in all quintiles. Of more interest, the difference level is significant for all but the largest quintile, which is consistent with the relative safe nature (i.e., moderate stock price movement) of this group of securities.

To this point, our preliminary analyses suggest that investors do not reallocate resources among industries as a result of SAD; however, the findings do suggest that small and large capitalization equities may be impacted differently. Nonetheless, the confidence in these results must be tempered as they effectively assume the influence of SAD is the same on each day throughout Fall and Winter, which is in contrast to the asymmetric relation documented in previous literature. Further, we have yet to control for other behavioral issues that are known to influence equity returns. Thus, we must turn to more statistically robust analyses before we make any definitive conclusions.

RESULTS

We begin by examining the total sample for the 48 industries using the following fixed effects equation:

$$Ret_{i,t} = \alpha + \beta_{Ind} + \beta_1 SAD_t + \beta_2 Fall_t + \beta_3 TYDum_t + \beta_4 Monday_t + \beta_5 Friday_t + \beta_6 Temp_t + \beta_7 Prcp_t + \beta_8 Jan_t + \beta_{Year} + \varepsilon \quad (2)$$

where $Ret_{i,t}$ is the daily holding period return for each industry. Our primary independent variables of interest are *SAD* and *Fall*, both of which follow our previous definitions.

B_{Ind} and β_{Year} are vectors of dummy variables representing industry and year, respectively. *TYDum* is a dummy variable equal to one if the observation day is one of the last ten or first ten of a calendar year and controls for the notion of tax-loss selling and/or window dressing that may occur around the end of a calendar year.[10] While an extensive discussion of these two hypotheses are beyond the scope of this work, both have the implication that investors, particularly institutional, sell off their "losers" at year end to capitalize on the loss in some way and then repurchase the same (or, at a minimum, the same type) of securities at the onset of the next year to capitalize on subsequent gains due to the potential underpriced nature of such securities.[11] Thus, any seasonal effects found during the turn-of-the-year period could be a result of this activity rather than attributable to seasonal depression and, thus, must be controlled for.

The "Monday effect" and "Friday effect" anomalies may also have an impact, thus we include dummy variables (labeled *Monday* and *Friday*) as controls.[12] We also include the average temperature (*Temp*) and rainfall, in inches, (*Prcp*) for each day as controls for other weather-related influences that have been documented to affect stock markets.[13]

Since stock returns may be correlated over time, serial autocorrelation is a common issue when dealing with panel data. Thus, prior to estimating the equations, we implemented the Wooldridge test for autocorrelation, finding a significant test statistic, which indicates the need to control for this potentially biasing issue.[14] We therefore redefine our equations by incorporating an AR(1) disturbance. To insure that we have adequately addressed the issue of autocorrelation we also calculate the Baltagi and Wu (1999) Least Biased Instrument (LBI) statistic for each regression. Results of our estimations are presented in Table 4. Since significant autocorrelation still exists at levels of LBI significantly lower than 2.0, it appears the AR(1) model specification has sufficiently corrected for potential biases.

The coefficient on *TYDum* is positive and significant in all specifications, as is the influence of *Temp* and *Prcp*, suggesting the effects of all three are much the same across all categories.[15] We find, as expected, a negative and highly significant coefficient on *Monday*, reflective of the historically significant average negative return on the first day of the week. Likewise, we find a positive and significant coefficient on *Friday*, which again is consistent with our expectations.

The primary variables of influence, *SAD* and *Fall*, are extremely consistent throughout the four segmentations. Specifically, all indicate a positive *SAD* coefficient and a negative *Fall* coefficient, both of which are consistent with that found in KKL. In fact, there appears to be virtually no difference between the risky and safe industries in regards to the proxies for seasonal depression. The evidence indicates that the shift away from risky securities (due to SAD) in the Fall and the subsequent reversal in the Winter is generally prevalent throughout all industries, regardless of perceived or historically measured risk classification. In sum, there appears to be no support for the notion that SAD-afflicted investors shift resources among industries within the equity market.

Turning to the size analysis, we implement the same model (absent the fixed effects) on the samples segmented by size quintiles, as based on the asset's market capitalization. Results are presented in Table 5. The significance disappears for both the temperature and precipitation variables. In addition, *Jan* is only significant for the smallest quintile of securities, which is again consistent with the "small-firm January effect" that has been documented in previous literature (e.g., Haug and Hirschey, 2006). In a similar fashion (and with similar reasoning), *TYDum* is highly significant for the smallest 40% and marginally significant for the third quintile, but insignificant for the largest 40% of the sample. The Monday effect is consistent across all size quintiles, while the same is true for the Friday effect, save the largest quintile.

Finally, and most importantly, the asymmetric relationship as previously found in the total sample is replicated in the four smallest quintiles. However, in the largest quintile, we find an insignificant coefficient on *Fall* and only a marginally significant coefficient on *SAD*. These findings can be interpreted as support for the hypothesis of a different SAD effect dependent upon the underlying risk (as proxied by size) of the investment class. Specifically, since smaller capitalization securities are typically considered less risky, we might expect to find the influence of SAD to be most prevalent. In contrast, the largest equity securities are typically considered to be safer in nature; therefore, we would expect little influence from SAD. Thus, to the extent that investors reallocate portfolios from equity to debt, it appears they do so by liquidating small capitalization, rather than large capitalization, equity investments.

CONCLUSION

Prior studies find an asymmetric relationship around the Winter solstice, which they attribute to Seasonal Affective Disorder (SAD). This finding is further strengthened by the evidence that investors shift resources away from risky equities and towards safer alternatives such as debt in the Fall and reverse the positions in the Winter. While this shift between asset classes appears significant, no prior study has yet examined whether investors also shift resources among equity sectors in response to seasonally induced depression. We fill this gap, finding that such a movement does not generally appear to occur, suggesting investors impacted by SAD treat all equity sectors as similar with regard to risk. Specifically, we find the documented SAD affect is persistent throughout both safe and risky industries, as defined by both subjective and quantitative methods.

We also examine whether such a reallocation from equity to debt is related to the market capitalization of the equity. We find consistent results, with the only exception being an insignificant relation between SAD’s influence and the returns for the largest 20% of equities. Thus, it appears that any shift in allocation is driven by a liquidation of smaller capitalization securities, implying that large capitalization stocks are generally viewed as less risky investments.

NOTES

1. For example, Lakonishok, Shleifer, Thalor, and Vishny (1991) propose the “window-dressing” hypothesis, the effect of which can be more pronounced in small firms.
2. It is estimated by Rosenthal (1998) that approximately 10 million people suffer from SAD, with an additional 15 million afflicted by the milder “Winter Blues.”
3. Molin et al. (1996) and Young et al. (1997) document that SAD is directly associated with sunlight.
4. For example, Carton et al. (1995) conclude depression increases the general level of pessimism, and, as a result, individuals are more reluctant to make riskier decisions.
5. Perhaps most notably, KKL examine countries in both hemispheres and find the effects of SAD to be exactly opposite, which would be expected given the opposing seasons.
6. The calculation for determining the length of night involves standard approximations for spherical trigonometry. See KKL for a complete description of the process.
7. For completeness, we examine an alternative specification for SAD, where $SAD = (H_t - 12)$ for the entire year rather than just during the Fall and Winter. The results are qualitatively unchanged.
8. The industry at the median is omitted, as is the always present “other” category, which we cannot accurately classify as either safe or risky.
9. We thank Kenneth French for making these data available on his website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. In addition, more in-depth definitions are available at the site.
10. See Ritter (1988) and Haugen and Lakonishok (1988) for a discussion of the tax loss selling and window dressing hypotheses, respectively.
11. Evidence of both hypotheses has been documented in the literature. For example, see Musto (1997) and Maxwell (1998) on window dressing, and Sias and Starks (1997) and Poterba and Weisbenner (2001) on tax-loss selling.
12. See Pettingill (2003) for an in-depth discussion of the effects.
13. The measurements are taken in New York City and are obtained from the National Climatic Data Center (NCDC).
14. See Wooldridge (2002) and Drukker (2003) for further discussion.
15. Previous literature is somewhat inconsistent regarding the influence of other weather factors on stock market returns. For example, Cao and Wei (2005) find a negative relation between temperature and returns, while KKL find a positive (although not always significant) coefficient. KKL also finds an insignificant relation between returns and precipitation in US stock markets.

Table 1: Summary Statistics of Fama-French 48 Sectors

The following table presents summary statistics for the entire sample of the Fama-French (FF) 48 Sectors for the time period 1963 to 2007. *Return* is the average daily holding period return for the respective sector. *Volatility* is the average 3-year rolling standard deviation. *R* and *S* designate risky and safe sectors, respectively. Designations in the subjective column are the authors' opinion. Designations in the quantitative column are based upon segmentation above and below the median values of *Volatility*. The sector at the median was omitted for the Quantitative designations.

Sector	Return	Volatility	Subjective	Quantitative
Agric	.054	1.201	S	R
Food	.051	0.826	S	S
Soda	.056	1.362	S	R
Beer	.055	1.117	S	S
Smoke	.068	1.347	S	R
Toys	.037	1.438	R	R
Fun	.064	1.435	R	R
Books	.046	0.964	R	S
Hshld	.046	1.055	S	S
Clths	.045	1.047	R	S
Hlth	.045	1.570	S	R
Drugs	.052	1.082	S	S
Chems	.044	1.027	S	S
Rubbr	.048	1.014	S	S
Txtls	.043	1.018	S	S
Bldmt	.045	0.966	S	S
Cnstr	.051	1.320	S	R
Steel	.040	1.211	S	R
Fabpr	.028	1.280	S	R
Mach	.045	1.043	S	S
Elceq	.060	1.224	S	R
Autos	.039	1.232	R	R
Aero	.056	1.261	R	R
Ships	.045	1.281	S	R
Guns	.055	1.366	S	R
Gold	.052	2.108	S	R
Mines	.055	1.197	S	R
Coal	.069	1.731	S	R
Oil	.056	1.102	S	S
Util	.041	0.678	S	S
Telcm	.041	0.976	R	S
Persv	.034	1.218	R	R
Bussv	.052	1.192	R	R
Comps	.049	1.514	R	R
Chips	.049	1.454	R	R
Labeq	.048	1.351	R	R
Paper	.045	1.022	S	S
Boxes	.048	1.136	S	S
Trans	.043	1.113	S	S
Whlsl	.048	0.981	R	S
Rtail	.049	1.054	R	S

Table 1: Summary Statistics of Fama-French 48 Sectors (Continued)

Sector	Return	Volatility	Subjective	Quantitative
Meals	.055	1.212	R	R
Banks	.046	1.021	R	S
Insur	.048	0.950	R	S
Rlest	.025	1.123	R	S
Fin	.058	1.066	R	S
Medeq	.056	1.142	S	NA
Other	.031	1.342	NA	NA
Total Sample	.048	1.200		
SRisky	.047	1.184		
SSafe	.050	1.198		
QRisky	.050	1.370		
QSafe	.047	1.017		

Table 2: SAD versus Non-SAD Periods

The following table presents summary statistics for average daily returns by sector. Panel A is for the comparison of SAD periods (Fall and Winter) and non-SAD periods (Spring and Summer). Panel B is for the comparison of Fall and Winter. The final column in each panel provides results from a t-test between the two samples.

	Panel A			Panel B		
Sector	SAD	Non-SAD	*t*-stat	Fall	Winter	*t*-stat
Agric	.082	.027	2.35	.038	.128	-2.55
Food	.067	.036	1.88	.077	.055	0.91
Soda	.094	.021	2.76	.064	.124	-1.54
Beer	.075	.037	1.80	.056	.096	-1.27
Smoke	.081	.056	0.94	.092	.069	0.60
Toys	.062	.014	1.77	-.024	.152	-4.32
Fun	.114	.018	3.45	.061	.169	-2.62
Books	.073	.022	2.72	.037	.110	-2.55
Hshld	.068	.026	2.03	.060	.075	-0.46
Clths	.084	.009	3.66	.024	.147	-4.02
Hlth	.056	.035	.66	.014	.100	-1.86
Drugs	.065	.041	1.13	.062	.067	-0.17
Chems	.066	.023	2.13	.038	.096	-1.90
Rubbr	.082	.017	3.36	.025	.142	-4.08
Txtls	.072	.015	2.81	.017	.129	-3.75
Bldmt	.088	.006	4.37	.044	.133	-3.17
Cnstr	.086	.018	2.64	.038	.135	-2.58
Steel	.077	.006	2.89	.007	.149	-3.79
Fabpr	.051	.007	1.79	.000	.104	-2.90
Mach	.077	.016	2.96	.023	.133	-3.56
Elceq	.086	.035	2.16	.074	.098	-0.68
Autos	.056	.022	1.43	-.013	.128	-3.93
Aero	.080	.033	1.95	.051	.111	-1.68
Ships	.050	.041	0.36	.009	.092	-2.24
Guns	.055	.055	0.00	.021	.090	-1.77
Gold	.044	.059	-0.37	-.022	.113	-2.24
mines	.081	.030	2.11	.015	.149	-3.74
Coal	.099	.041	1.66	.072	.128	-1.11
Oil	.054	.057	-0.12	.042	.067	-0.76
Util	.052	.031	1.54	.068	.035	1.63
Telcm	.063	.020	2.22	.061	.065	-0.14
Persv	.051	.018	1.42	.027	.076	-1.42
Bussv	.086	.020	2.80	.062	.111	-1.41
Comps	.077	.022	1.82	.059	.096	-0.80
Chips	.073	.026	1.57	.031	.116	-1.99
Labeq	.080	.019	2.29	.046	.115	-1.79
Paper	.075	.018	2.90	.050	.100	-1.68
Boxes	.084	.015	3.11	.066	.102	-1.06
Trans	.078	.009	3.24	.052	.105	-1.67
Whlsl	.077	.021	2.94	.035	.120	-3.09
Rtail	.070	.028	2.02	.018	.125	-3.42

Table 2: SAD versus Non-SAD Periods (Continued)

	Panel A			Panel B		
Sector	SAD	Non-SAD	*t*-stat	Fall	Winter	*t*-stat
Meals	.085	.027	2.49	.044	.127	-2.43
Banks	.060	.033	1.34	.031	.090	-1.95
Insur	.067	.031	1.97	.062	.072	-0.36
Rlest	.060	-.007	3.07	-.025	.149	-5.40
Fin	.089	.029	2.63	.068	.110	-1.30
Medeq	.073	.040	1.53	.060	.087	-0.85
Other	.064	.000	2.45	.031	.099	-1.78
Total Sample	.0728	.0259	13.52	.039	.108	-13.56
SRisky	.0741	.0214	10.85	.036	.114	-10.76
SSafe	.0716	.0303	8.35	.041	.103	-8.49
QRisky	.0742	.0282	8.13	.033	.117	-9.97
QSafe	.0715	.0231	11.60	.043	.101	-9.32

Table 3: SAD versus Non-SAD Periods for portfolio based on size quintile

The following table presents summary statistics for average daily returns of portfolios by size quintile. Panel A is for the comparison of SAD periods (Fall and Winter) and non-SAD periods (Spring and Summer). Panel B is for the comparison of Fall and Winter. The final column in each panel provides results from a *t*-test between the two samples.

	Panel A			Panel B		
Portfolio by Size	SAD	Non-SAD	*t*-stat	Fall	Winter	*t*-stat
Quintile 1 (Small)	.079	.019	3.95	.000	.162	-7.34
Quintile 2	.077	.025	3.07	.028	.128	-4.05
Quintile 3	.074	.027	2.86	.036	.114	-3.23
Quintile 4	.073	.028	2.72	.045	.102	-2.31
Quintile 5 (Large)	.060	.026	1.95	.051	.071	-.75

Table 4: Fixed Effects Models: Risk Levels

The following table presents results from the following fixed effects model, with AR(1) disturbances for the FF 48 industries:

$$Ret_{i,t} = \alpha + \beta_{Sect} + \beta_1 SAD_t + \beta_2 FallDum + \beta_3 TYDum + \beta_4 Monday + \beta_5 Friday + \beta_6 Temp + \beta_7 Prcp + \beta_8 Jan + \beta_{Year} + \varepsilon$$

where *Ret* is the percentage daily return for each respective FF sector. β_{Sect} and β_{Year} are vectors of dummy variables to control for the sector and year of observation, respectively. *SAD* is calculated as [H – 12] during fall and winter, zero otherwise, where H is the number of hours of night for the given day of issuance. *FallDum* is a dummy variable equal to one if the observation is during the fall (i.e., September 21 to December 20). *TYDum* is a dummy variable equal to one if the observation day is one of the last ten days of December or the first ten days of January. *Monday* (*Friday*) is a dummy variable equal to one if the observation day is a Monday (Friday). *Temp* is the average daily temperature for the date of observation. *Prcp* is the total amount of precipitation during the date of observation. *Jan* is a dummy variable equal to one if the observation is in January.

	Total		*SSafe*		*SRisky*		*QSafe*		*QRisky*	
	Coef	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
Intercept	-0.18	-8.32	-0.20	-6.01	-0.17	-5.76	-0.17	-7.10	-0.20	-5.20
SAD	0.03	10.45	0.03	7.24	0.03	7.57	0.03	7.57	0.04	7.13
FallDum	-0.05	-7.49	-0.05	-5.19	-0.06	-5.43	-0.05	-5.12	-0.06	-5.41
TYDum	0.07	6.08	0.08	4.78	0.06	3.77	0.06	3.72	0.09	4.79
Monday	-0.15	-19.83	-0.14	-13.28	-0.15	-14.84	-0.14	-15.82	-0.16	-12.62
Friday	0.04	9.45	0.05	7.74	0.03	5.57	0.04	7.80	0.05	6.23
Temp	0.00	6.61	0.00	4.86	0.00	4.47	0.00	5.18	0.00	4.28
Prcp	0.00	3.56	0.00	1.81	0.00	3.24	0.00	3.00	0.00	2.25
Jan	-0.03	-2.48	-0.04	-2.77	-0.01	-0.73	-0.03	-2.26	-0.02	-1.26
N	524,917		267,317		257,600		257,600*		256,117*	
F-value	132.81(*p*=.0000)		62.47(*p*=.0000)		71.80(*p*=.0000)		75.45(*p*=.0000)		60.12(*p*=.0000)	
BW LBI	1.86		1.88		1.85		1.82		1.89	

*Note: For 48 industry classification, the sample size of *QRisky* is smaller than *QSafe* because Hlth, classified as risky by quantitative measure, has missing values from 1963/07/01 to 1969/06/30.

Table 5: Fixed Effects Models: Size

The following table presents results from the following fixed effects model, with AR(1) disturbances for the portfolio by size:

$$Ret_{i,t} = \alpha + \beta_1 SAD_t + \beta_2 FallDum + \beta_3 TYDum + \beta_4 Monday + \beta_5 Friday + \beta_6 Temp + \beta_7 Prcp + \beta_8 Jan + \beta_{Year} + \varepsilon$$

where *Ret* is the percentage daily return for each respective size quintile portfolio. β_{Year} is vector of dummy variable to control for the year of observation. *SAD* is calculated as [H – 12] during fall and winter, zero otherwise, where H is the number of hours of night for the given day of issuance. *FallDum* is a dummy variable equal to one if the observation is during the fall (i.e., September 21 to December 20). *TYDum* is a dummy variable equal to one if the observation day is one of the last ten days of December or the first ten days of January. *Monday* (*Friday*) is a dummy variable equal to one if the observation day is a Monday (Friday). *Temp* is the average daily temperature for the date of observation. *Prcp* is the total amount of precipitation during the date of observation. Jan is a dummy variable equal to one if the observation is in January.

	Quintile 1 (Small)		*Quintile 2*		*Quintile 3*		*Quintile 4*		*Quintile 5(Large)*	
	Coef	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*	*Coef*	*t-stat*
Intercept	-0.04	-0.68	0.00	-0.06	0.04	0.70	0.02	0.41	0.03	0.56
SAD	0.04	3.18	0.05	3.64	0.04	3.50	0.04	3.32	0.02	1.68
FallDum	-0.08	-3.18	-0.07	-2.59	-0.07	-2.36	-0.06	-2.01	-0.02	-0.61
TYDum	0.18	4.10	0.11	2.18	0.09	1.86	0.07	1.36	0.03	0.51
Monday	-0.19	-9.26	-0.18	-7.85	-0.16	-7.02	-0.15	-6.52	-0.08	-3.26
Friday	0.13	6.52	0.06	2.76	0.05	2.13	0.04	1.63	-0.01	-0.27
Temp	0.00	1.08	0.00	0.96	0.00	0.51	0.00	0.75	0.00	0.32
Prcp	0.00	0.87	0.00	0.83	0.00	0.66	0.00	0.70	0.00	0.55
Jan	0.09	2.54	-0.01	-0.32	-0.05	-1.20	-0.06	-1.45	-0.02	-0.37
N	10,058		10,058		10,058		10,058		10,058	
Adj. R-sq	.0362		.0154		.0107		.0075		.0008	

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