

# SAD Investors: Implications of Seasonal Variations in Risk Aversion

by

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# **SAD Investors: Implications of Seasonal Variations in Risk Aversion**

## **Abstract**

Previous research has shown that stock market returns appear to be associated with variations in the incidence of seasonal affective disorder, SAD, during the fall and winter. The medical and psychology literatures have clinically established a positive relationship between the length of night and depression through the seasons, as well as a positive relationship between depression and risk aversion. A seasonal pattern exists in stock returns, consistent with SAD-influenced individuals buying and selling risky assets in response to changes in their levels of risk aversion caused by seasonal depression. The present paper considers whether SAD is associated with seasonalities in other financial markets, specifically returns on government bonds, returns on stock portfolios of different risk classes, and flows of capital into and out of mutual funds of different risk. We show statistically and economically significant evidence from considering these other measures, consistent with a widespread, SAD-influenced seasonal movement of investment funds into and out of various investment vehicles.

In a recent paper, Kamstra, Kramer, and Levi (2003, henceforth KKL) show that there is an economically and statistically significant seasonal regularity in stock market returns that is consistent with the influence of seasonal affective disorder (SAD) on investors during the fall and winter. Specifically, KKL argue that stock returns are influenced when many people are suffering from depression due to SAD, or the milder “winter blues,” as a result of increased length of night (or equivalently, reduced length of day) in the fall and winter. Clinical and experimental studies in the medical, psychology, and economics literatures indicate that seasonal reduction in hours of daylight leads to depression for many people, and further studies show depression leads to heightened risk aversion. KKL hypothesize that increased risk aversion among SAD-affected investors in the fall causes those investors to sell risky stock, and then investors resume risky holdings with the reduction in risk aversion that comes with increasingly abundant daylight in the new year. KKL find a striking annual cycle in international stock market returns consistent with their hypothesis, even after controlling for established market seasonalities such as tax-loss selling and potentially relevant environmental factors such as temperature and cloud cover. Stock market returns are lowest on average during the fall months when the number of hours of daylight is falling toward its annual minimum. Mean stock returns are then highest as daylight becomes more plentiful in the new year. In addition, the annual stock market return cycle due to SAD has greater amplitude at higher latitudes where the variations in length of night across seasons are greatest. Furthermore, the patterns in stock returns in Northern versus Southern Hemisphere markets are six months out of phase, as are the seasons.

If the SAD / depression / risk aversion hypothesis is correct, seasonal patterns should exist in other markets. For instance, the returns on relatively safe government bond indices should display a reverse seasonal relative to stock returns; the seasonal pattern in stock returns should be more pronounced in riskier classes of stocks; and there should be evidence of a seasonal pattern in the flow of funds between risky and safe assets.

The underlying returns model in which seasonality in equity and bond returns are the

mirror image of each other may be considered in the following way. Suppose there are two groups of investors, those who suffer from SAD and those who do not. Each group holds a portfolio containing equities and bonds. In the fall, SAD sufferers become depressed and consequently more risk averse, and they wish to hold relatively fewer equities and relatively more bonds. The preferences of the non-sufferers do not change with the season. Since all equities and bonds must ultimately be held, the non-sufferers must be persuaded to buy the equities that the SAD sufferers wish to sell, and to sell some of their bonds, the preference for which has not changed among the non-sufferers. Equity prices are depressed in the fall as a consequence of the reduced demand for equities by the SAD-sufferers, thereby raising expected equity returns. At the same time, increased demand for bonds by the SAD sufferers raises their prices in the fall, hence lowering their expected returns and increasing the willingness of the non-sufferers to sell their bonds to the other group. Equilibrium is restored with equities flowing from SAD to non-SAD investors and bonds flowing from non-SAD to SAD investors. The opposite happens in the spring as the days lengthen.

We aim to determine whether there are seasonal regularities in other parts of the capital market that are consistent with this model. Specifically, we seek answers to the following questions:

1. When people are experiencing changes in risk aversion as a consequence of SAD, initially selling stocks (leading to stock prices which rise less quickly in the fall than they would otherwise) and later repurchasing stocks (leading to higher prices and therefore higher returns in the winter), are stock sellers (buyers) simultaneously buying (selling) low or zero default-risk Treasury bonds, influencing the price of bonds and affecting their returns? That is, is the seasonal pattern of risk-free bond returns the reverse of the seasonal pattern of stock returns: low bond returns when stock returns due to SAD are highest, and vice versa?
2. When SAD sufferers are shunning risk, does this result in less willingness to hold the riskier end of the stock market spectrum than the safer end? In other words, does the

seasonal pattern of stock returns of different deciles of risk – measured by, for example, company beta (systematic risk) or standard deviation of returns (total risk) – match what we would expect from SAD, namely a larger amplitude of seasonal variation for the riskier companies and relatively muted seasonal variation for the less risky companies? A risk-related seasonal pattern in stock returns is suggested but not fully explored by KKL: they find SAD has a more pronounced effect on an equally-weighted aggregate stock market index than on a value-weighted index, with equal weighting placing greater relative importance on smaller (riskier) companies.

3. Do flows into and out of mutual funds reflect patterns that are consistent with the SAD hypothesis, with capital flowing out of risky stock funds and into safe bond funds during times when increased length of night leads to higher levels of risk aversion among affected individuals? Does capital flow out of bond funds and back into stock funds when daylight becomes more abundant?

Evidence from answering these questions would help clarify the importance of seasonal affective disorder for asset return regularities in financial markets.

The remainder of the paper is organized as follows. In Section 1, we discuss the medical condition of SAD and explain how SAD can translate into an economically significant influence on capital markets. In Section 2, we define the measure we use to capture the impact of SAD on financial markets. We present evidence in Section 3 that seasonal depression has an impact on bond market returns that is consistent with (and opposite to) the pattern that has been shown to exist in markets for risky stock. In Section 4 we consider risk-sorted stock deciles and determine that the magnitude of the SAD effect on returns varies directly with riskiness of the stock portfolio. In Section 5 we present evidence that the flow of capital into and out of mutual funds follows a seasonal pattern consistent with SAD. Section 6 concludes.

# 1 Seasonal Affective Disorder and Risk Aversion

There are two essential components to a link between seasonalities in length of night and different manifestations of risk aversion:

1. That seasonal variations in length of night result in seasonal variations in the incidence of depression and the less serious condition “winter blues.”
2. That variations in depression or winter blues are associated with variations in risk aversion; specifically, that risk aversion rises with depression.

Both of the above connections are well supported and extensively documented in clinical psychology and medical studies that consider both behavioral and biochemical evidence.

As for the impact of seasonal cycles in daylight on SAD, the evidence fills many books and research journals, where some of the journals are devoted to papers on affective (emotional) disorders, particularly of the seasonal variety. Indeed, there are numerous books telling people how to deal with this disorder, and many products which create “natural” light to help sufferers handle their condition. Examples of recent popular books devoted to considering seasonal affective disorder and therapies for dealing with it are Rosenthal (1998) and Lam (1998). Among the literally hundreds and perhaps thousands of journal articles on the pervasiveness and potential severity of SAD are papers by Cohen et. al. (1992), Faedda et. al. (1993), Molin et. al. (1996), and Young et. al. (1997). The large and growing volume of books, articles, and products dealing with seasonal affective disorder is testimony to the fact that this condition is a very real and extensive problem, estimated to influence at least 10 million Americans severely, 15 million Americans mildly, and many more millions in other countries ranging from those near polar extremes to those as close to the equator as India. Symptoms of SAD include anxiety, prolonged periods of sadness, chronic fatigue, difficulty concentrating, reduced energy, lethargy, sleep disturbance, sugar and carbohydrate craving with accompanying weight gain, loss of interest in sex, and of course clinical depression.<sup>1</sup>

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<sup>1</sup>For extensive references to the literatures covering these matters see Kamstra, Kramer, Levi (2003).

There is also a large and growing literature on the second link mentioned above, namely, between depression and risk taking behavior. This link has been documented in both financial and non-financial settings. The aspect of risk that is most commonly studied in the psychology literature is the tendency for depressed people to avoid being “sensation seekers.” In principle, depressed people could throw caution to the wind, or they could become conservative in their behavior. The evidence strongly supports the latter: depression is associated with reduced sensation seeking tendencies which in financial settings translates to increased risk aversion. For example, Carton et. al. (1992) test whether depressive mood reduces sensation seeking and conclude that it does. Horvath and Zuckerman (1993) consider both the connection between depression and sensation seeking and how depressed people evaluate risk. Two other papers by Zuckerman (1980, 1984) show how depression emerges as a correlate with reduced sensation seeking when considered in the context of other potential biological factors. Eisenberg, Baron, and Seligman (1998) consider individuals’ risk aversion and the role of anxiety in the willingness to take chances.

Examples of papers that explore the extension from sensation seeking into the financial context include Harlow and Brown (1990) and Wong and Carducci (1991). Wong and Carducci find that individuals who score low on tests of sensation seeking display greater risk aversion in making financial decisions, including the decision to purchase stocks, bonds, and automobile insurance. Harlow and Brown shed light on the link between sensation seeking and financial risk inclination by building on results from psychiatry which show that high blood levels of the enzyme monoamine oxidase are associated with depression and a lack of sensation seeking while low levels of monoamine oxidase are associated with a high degree of sensation seeking.<sup>2</sup> Harlow and Brown had 183 test subjects participate in sequences of first price sealed bid auctions. They determined the quantitative sensation seeking score for each subject and also measured participants’ blood levels of various neuroregulating enzymes. Summarizing the results of their parametric and non-parametric analyses, they state “Indi-

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<sup>2</sup>See Zuckerman (1983), Hirschfeld (2000), and Delgado (2000) for further discussion of the biochemistry of depression and sensation seeking.

viduals with neurochemical activity characterized by lower levels of the enzyme monoamine oxidase and with a higher degree of sensation-seeking are *more willing to accept economic risk* ... Conversely, high levels of this enzyme and a low level of sensation seeking appear to be associated with risk-averse behaviour.” (pages 50-51, emphasis added). These findings are consistent with an individual’s level of sensation seeking being indicative of his or her degree of financial risk aversion, an important link in the mechanism that ties the depression associated with seasonal affective disorder to widespread effects in financial markets.

## 2 Measuring the Impact of SAD

In order to evaluate the manifestation of seasonal variations in daily light and darkness on financial markets, we must first decide how to measure the causal variable.<sup>3</sup> We choose to use the length of the night at New York’s latitude, 41 degrees north. As KKL report, one could similarly use the latitude from a different location in the continental US. The fact that many market participants initiate trades from latitudes other than that of New York does not adversely affect the mechanism underlying the SAD hypothesis, as length of night follows a similar seasonal throughout a hemisphere, varying only in amplitude.

In this paper we focus on US evidence since we are investigating a range of market returns and mutual fund flows that are more readily available for the United States. To obtain the daily number of hours of night in New York, we first need to calculate the sun’s declination angle,  $\lambda_t$ :

$$\lambda_t = 0.4102 \cdot \sin \left[ \left( \frac{2\pi}{365} \right) (\text{julian}_t - 80.25) \right], \quad (1)$$

where julian varies from 1 to 365 (366 in a leap year), taking the value 1 for January 1, 2 for January 2, and so on. We can then calculate the number of hours of night,  $H_t$ , at latitude

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<sup>3</sup>Note that KKL (2003) find empirical evidence that the driving force behind the SAD effect they document is *length of night* (the time between sunset and sunrise), not *sunshine* (which varies according to percentage cloud cover). They find that additionally controlling for sunshine does not materially change the sign or significance of SAD-related variables or any other variables in their regressions. Further, the sunshine variable is typically statistically insignificant across the nine countries they consider.



$\delta$  (41 degrees):

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

where  $\arccos$  is the arc cosine. Note that when working with monthly, as opposed to daily data, we define  $H_t$  as the median monthly hours of night.

Medical practitioners have determined that depression and other symptoms associated with the most common form of SAD are isolated to the fall and winter. Symptoms of fall/winter SAD (commonly known as winter SAD) can start as early as autumn equinox and may persist as late as spring equinox, as discussed by Dilsaver (1990) and others. A rarer condition called summer SAD or reverse SAD affects about a fifth as many people as winter SAD, and it can cause symptoms that start in the spring and last as late as the end of summer. While the cause and effect of winter SAD are well documented, psychologists' understanding of summer SAD is still preliminary, with high temperature, not changes in the amount of daylight, thought to be the most likely trigger. In this paper, we investigate the financial implications of winter SAD only.

We define our SAD measure as follows, taking on non-zero values only during the seasons when the length of day is well understood to have an influence on individuals' behavior:

$$SAD_t = \begin{cases} H_t - 12 & \text{for trading days in the fall and winter} \\ 0 & \text{otherwise.} \end{cases} \quad (3)$$

By deducting 12 from the number of hours of night ( $H_t$ ),  $SAD_t$  measures the length of the night in winter and fall relative to the mean annual number of hours of night. (We define the SAD measure in terms of number of hours of night, the time from sunset to sunrise, though in principle one could instead define the measure in terms of number of hours of daylight.)

As defined, the SAD measure equals zero at fall equinox and spring equinox, and takes on positive values throughout the fall and winter months in between those two dates. Furthermore, the value of the SAD measure is roughly the same during days in December as it

is during days in January, the SAD variable takes on about the same values during days in November as it does on February days, and it is again about equal in value during the days in October as it is during the days of March. As we describe below, however, we expect the impact of seasonal depression on a given asset's returns to take on different values in the fall months versus the winter months. With equities, for instance, we expect SAD affected investors to sell riskier assets in the fall and then buy them back after winter solstice as their levels of risk aversion return to normal. As a consequence, equity prices should be lower in the fall than they would be without the elevated risk aversion amongst SAD affected investors. That is, with rising risk aversion in fall, we expect stock prices to rise less quickly relative to the rest of the year. Then, as daylight becomes more plentiful and risk aversion declines, SAD-influenced investors start resuming their holdings of risky assets, with the recovery of prices raising returns. Hence, we would expect *lower* stock returns in fall and *higher* stock returns in winter than would be expected in the absence of a SAD effect.

The SAD variable is itself incapable of capturing a pattern where opposing effects are expected across the fall and winter months, hence we additionally use a dummy variable for the fall:<sup>4</sup>

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

Inclusion of this dummy variable allows but does not require the impact of SAD to differ across the fall and winter seasons. The relevance of the difference in the magnitude of the SAD effect across the fall and winter can be judged by the magnitude and significance of this fall dummy variable. The total impact of seasonal depression on returns is measured collectively by the SAD variable and the fall dummy variable. This parameterization with two variables permits the impact of seasonal depression on returns in the fall months to differ from that in the winter months, as we expect.

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<sup>4</sup>We define the fall as September 21 through December 20 in the context of daily data, and October through December when working with monthly data.

### 3 The Bond Market

When investors become less willing to bear risk and perhaps liquidate portions of their stock portfolios, the implication is that the funds raised ought to be placed in relatively safer assets such as government bonds. Hence, when stock prices are declining (or rising less quickly) as a result of the trading activity of depressed individuals, bond prices may be rising. This suggests the seasonal stock and bond market patterns should be the reverse of one another during the fall and winter seasons when length of night influences investor sentiment.<sup>5</sup>

To investigate whether there are reverse seasonal patterns in the stock and bond markets related to SAD, we consider returns to holding US Treasury bonds. We choose US government bonds because they represent the least risky of fixed income securities and hence are likely to be seen by investors as the favored alternative to risky equities. We select return indices for various Treasury bond maturities ranging from 1 year to 10 years, where the returns include interest and capital gains/losses. These data are obtained from the Center for Research on Security Prices (CRSP) US Treasury and Inflation Series. The series contain returns from the CRSP US Treasury Fixed Term Index Series and the CRSP Risk Free Rates File. The frequency of the returns is monthly.

In Table 1, we present summary statistics on the monthly Treasury bond index returns. Each series begins in January, April, or May 1941, as available through CRSP. The series all end in December 2001. The mean monthly returns and return standard deviations typically increase with maturity. Average returns from holding the various government bond series are slightly below one-half percent per month. That is, average annual returns on risk-free US Treasury bonds over the last 60 years are approximately five percent. Returns vary substantially from month-to-month on all maturity bonds, especially for the longer maturity bonds, with some months' losses being around seven percent and some months' returns well

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<sup>5</sup>While some market circumstances, such as bad news about the economy, can cause the bond and stock markets to move in opposite directions, there are other events, such as interest rate movements, that can make them move in the same direction. Our emphasis here is on *seasonal* regularities in bond and stock markets, unrelated to exogenous macroeconomic shocks.

over ten percent. Of course, these large gains and losses are due to variations in the bond prices. As in the stock market, returns are skewed to the right and leptokurtotic.

Since we hypothesize that the SAD seasonal in bond returns will be opposite in sign relative to stock returns, it is helpful to consider first whether our monthly bond index returns are unconditionally correlated with stock returns. If stock and bond returns are highly negatively correlated, then it may not be surprising to find bond returns display an opposite SAD seasonal relative to stock returns. If, however, there is positive correlation between stock and bond returns, then finding opposite SAD seasonals in bond returns relative to stock returns would be all the more remarkable. Table 2 contains correlation coefficients based on the covariance between the each of the monthly government bond index returns and monthly CRSP total stock market index returns for various sample periods. Note that for the full sample period, the bond returns are significantly positively correlated with stock returns. In each of the decade sub-periods, stock and bond returns are either significantly positively correlated or insignificantly negatively correlated, with the single exception of the 5 year bond index in the 1950s. Thus we can safely assert that the tests we present below for an opposite SAD seasonal in bonds relative to stocks are not unduly biased in favor of the result we expect.

In Figure 1 we plot the average monthly percentage returns on the bonds we consider, expressed on an annualized basis. Omitted plots based on individual monthly bond returns, as opposed to the average returns across the series, are very similar. Note the returns we plot are unconditional; conditional analysis is presented later. Returns are very high in the fall months, September, October, and November. Returns drop through the winter, reaching a low in February. The difference in the average returns from October to February is particularly striking: about 7 percent on an annualized basis. The overall pattern is consistent with investors moving funds into safe government bonds in the fall, driving up prices and hence returns, and then moving funds out of government bonds with the increase

in daylight that commences with winter, lowering returns.<sup>6</sup>

To more fully evaluate the quantitative impact of SAD on bond returns, we estimate a set of regressions for the bond return indices, allowing the magnitude of the SAD coefficient to differ across indices. Based on the seasonal cycle of SAD, we expect to find patterns that are opposite to those found by KKL for stock market returns: when SAD-induced changes in risk aversion cause stock returns to rise, bond returns should fall, and vice versa. We estimate the following model, controlling for well-known market seasonals:<sup>7</sup>

$$r_{i,t} = \mu + \rho_{i,1}r_{i,t-1} + \mu_{i,SAD}SAD_t + \mu_{i,Fall}D_t^{Fall} + \mu_{i,Tax}D_t^{Tax} + \epsilon_{i,t} \quad (5)$$

Variables are defined as follows:  $r_{i,t}$  is the month  $t$  return for a given bond index ( $i$  indicates the bond series, with 1, 2, 5, 7, or 10 year maturity),  $r_{i,t-1}$  is a lagged dependent variable,  $SAD_t$  equals  $H_t - 12$  during fall and winter months (October through March) and equals zero otherwise (where  $H_t$  is the median monthly number of hours of night in period  $t$ ),  $D_t^{Fall}$  is a dummy variable which equals one when month  $t$  is in the fall (October, November, and December) and equals zero otherwise, and  $D_t^{Tax}$  equals one for the month of January and equals zero otherwise. We report below results of testing the one-sided null hypotheses that  $\mu_{SAD} < 0$  and  $\mu_{Fall} > 0$ , with the inequalities suggested by evidence from the medical, psychology, and experimental economics literatures discussed in the previous sections. Note, however, that throughout the paper we conservatively report significance based on two-sided tests.

The five bond return series, for the 1, 2, 5, 7, and 10 year bonds, form a panel-time-series data set. Estimating Equation 5 jointly across the indices using Hansen's (1982)

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<sup>6</sup>The relatively smoother behavior of returns during the spring and summer months, April through August, is beyond the scope of this study. We focus on the fall and winter (September through March), the seasons during which the effects of length of day on mood are well understood by medical professionals.

<sup>7</sup>Some of the papers that document seasonalities in returns of various classes and maturities of bonds include the following. Schneeweis and Woolridge (1979) document the presence of autocorrelation in bond index returns. Schneeweis and Woolridge (1979), Chang and Huang (1990), and Wilson and Jones (1990) demonstrate the presence of a January seasonal in various US bond returns. While we don't consider daily bond returns in this study, Jordan and Jordan (1991) find there is no evidence of a day-of-the-week effect in corporate bonds over the past few decades.

GMM, we can exploit the covariance of the five series to provide more precise estimates of the SAD and fall effects.<sup>8</sup> Table 3 contains estimation results. In Panel A we provide parameter estimates and t-statistics based on Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. The series all display significant first order autocorrelation,<sup>9</sup> and the January/tax seasonal is significant for all the series. The SAD variable is everywhere significantly negative and the fall dummy is everywhere significantly positive. At the bottom of Panel A we provide the value of  $R^2$  for each index as well as the value of Lagrange Multiplier  $\chi^2$  statistics testing for the presence of up to twelve lags (a year) of residual autocorrelation or ARCH. Our use of HAC standard errors is justified by the mostly significant evidence of both ARCH and autocorrelation, commonly observed features of financial data.

When considering multiple variables, in this case the SAD and fall variables, it can be helpful to consider their joint significance. Two variables which are individually strongly significant may be less significant jointly, however that is not the case here. The Wald  $\chi^2$  test statistic in Panel B, based on the HAC covariance estimates, tests the joint significance of the SAD and fall variables across the bond series. We strongly reject the null that the SAD and fall coefficients are jointly zero.

Starting in 1980, the US Treasury began holding its security auctions on a pre-announced date every February, May, August, and November. The change was part of a concerted effort by the Treasury to avoid failed offerings by facilitating market participants' efforts to accumulate cash in preparation for the auction. To ensure our results are not driven by features of the data observed prior to the Treasury's effort to stabilize bond offerings, we also ran regressions on the post-1979 sub-period. Results for the post-1979 sub-period are as follows: while every coefficient related to the level of interest rates nearly doubled, reflecting

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<sup>8</sup>Results based on estimating Equation 5 separately for *each* index (as opposed to jointly using GMM) yields very similar results, in spite of the loss in power that may result from ignoring the covariance structure of errors across the bond return indices. These results are available from authors on request.

<sup>9</sup>While the HAC standard errors we use are robust to failing to control for autocorrelation, we include a lagged dependent variable in our estimation because the trend to maturity in bond prices and hence returns is very high for the shorter series (since the fixed terminal price is near).

the higher average interest rates post-1979, the signs, relative magnitudes and statistical significance of all the model coefficient estimates including the SAD and fall variables remained virtually unchanged with no qualitative differences compared to the results reported for the full sample. These results are available from the authors.

To enable discussion of the magnitude of the parameter estimates on the SAD and fall dummy variables that arise from estimating Equation 5, we present in Table 4 the translation of the SAD and fall parameter estimates into average annualized percentage returns. The first value we present for each bond index in Table 4 is the total average annualized return, which is between five and six percent for all the series. In the next column we present the portion of the average annualized return that is explained by the SAD measure. To compute the return due to SAD for a given index, we first calculate the value of the SAD variable for each month. We multiply each month's value by the index's SAD variable estimate shown in Table 3. We then compound across months, annualizing the result. In the last column, we present the average annualized return due to the fall dummy variable for each index, calculated by taking the value of the fall dummy variable for each month (one during months in the fall, zero otherwise) multiplying by the value of the fall dummy variable estimate for a particular index (from Table 3), compounding across months, converting the result into an annualized return.

For each value in Table 4, two and three asterisks denote significance at the 5 percent and 1 percent levels respectively, based on two-sided tests. In the case of the unconditional return column, significance is based on t-tests for a mean return different from zero. In the case of the columns for the annualized returns due to the SAD and fall dummy variables, significance is simply carried over from the t-tests on the parameter estimates shown in Table 3.

In a similar analysis of annual *stock market* returns due to the SAD and fall variables, KKL showed that the portion of returns due to SAD was significantly *positive* for most indices (in some cases exceeding the unconditional annual return itself) and the portion

of annual returns due to the fall variable was significantly *negative* for most stock indices considered. Those results are consistent with SAD-affected investors selling risky stock in the fall as they become less tolerant of risk, then resuming risky holdings after winter solstice, as they return to their non-SAD-affected level of risk tolerance.

The results in Table 4 provide further corroboration of SAD influencing investors' portfolio allocation decisions. The annual return due to SAD is significantly negative for all the bond indices we consider, opposite to the sign for risky equities. The extent of the annual return due to SAD ranges from about -1.92 percent per annum for the 10 year index to -0.78 percent per annum for the shortest term index we consider. The annual return due to the fall dummy is significantly positive in all cases, again opposite in sign relative to risky equities, ranging from a high of 1.7 percent for the 10 year Treasury bond series to a low of 0.53 percent for the 1 year series. The signs of the annual returns due to SAD and due to the fall dummy are consistent with SAD-affected investors moving assets out of stocks and into bonds during the period of increasing risk aversion, then moving out of bonds back into stocks once daylight becomes more plentiful and investors' degree of risk aversion reverts to more normal levels. The magnitudes of the annual bond returns due to SAD and the fall dummy suggest that the phenomenon is economically significant, each representing a substantial portion of the total annual returns to bonds. Furthermore, the overall impact from the SAD and fall variables is that bond returns are shifted from the winter into the fall, which is the mirror image of the effect in stock markets documented by KKL, in spite of the strong positive correlation between stock and bond index returns.

The larger magnitude of the SAD effect on longer maturity bonds suggests SAD-affected investors view the longer bonds as the relatively safer alternative to stocks when they become more risk averse, indicating that investors may be seeking the stability of income provided by longer bonds. That is, a risk averse investor facing a choice between purchasing 10 year bonds versus purchasing 1 year bonds annually for 10 years might prefer the 10 year bonds



to reduce the reinvestment uncertainty that arises every year for 1 year bonds.<sup>10</sup>

We conducted a variety of robustness checks. First, considering very short term (30-day and 90-day) Treasury bills and very long term (20 year and 30 year) Treasury bonds leads to results that are virtually indistinguishable from those presented above, with identical signs and statistical significance for the SAD and fall variables. Second, results for *daily* government bond indices (which are available to us only for relatively shorter time periods) are also qualitatively identical to those we report above based on monthly data. Detailed results are available from the authors on request.

## 4 Stock Portfolios of Differing Risk Class

If investors show changes in risk aversion associated with length of night, then this phenomenon should reveal itself differently in stock portfolios with different amounts of risk. Specifically, the riskier is the stock portfolio, the greater should be the size of the fluctuation in returns due to SAD. Results reported in a supplemental appendix to KKL (2003)<sup>11</sup> are suggestive of differences in the SAD-related seasonality across portfolios of differing risk class: SAD effects are more prominent in equal-weighted stock indices than in value-weighted stock indices, consistent with equal-weighted indices' relatively disproportionate representation of small, risky firms. In this paper we directly investigate whether the SAD seasonal is stronger in riskier portfolios.

We consider two measures of portfolio risk for examining the connection between risk and return suggested by SAD: the magnitude of the portfolio beta and the standard deviation of returns. Papers that consider stock portfolios sorted by beta or return standard deviation include Fama and French (1992), Kothari, Shanken and Sloan (1995), and many others. One procedure to consider possible differences in the size of various seasonalities exhibited by portfolios of different risk or overall return volatility is to consider the return on the

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<sup>10</sup>See Telser (1967) for further details on the argument that individuals who prefer certainty of income, perhaps for retirement planning, would prefer longer-lived assets.

<sup>11</sup>The appendix is available on the Web at [www.markkamstra.com](http://www.markkamstra.com).

extremes of the categorization deciles/quintiles.<sup>12</sup> For example, returns on the quintile of largest firms minus returns on the quintile of smallest firms can be examined for seasonality, an approach that has been applied specifically in the study of turn-of-year effects, as by Reiganum (1983), Rogalski and Tinic (1984) and Thaler (1987). In this paper we report the full spectrum of results based on estimating the SAD effect in all the CRSP return deciles sorted according to firms' beta or standard deviation of returns, which according to CRSP are constructed with equal-weighted returns.

In Table 5 we present summary statistics on daily CRSP decile returns, sorted on the basis of beta in Panel A and sorted by the standard deviation of returns in Panel B. The daily data span July 3, 1962 through December 31, 2001. Decile 1 denotes the category of firms with the highest beta or return standard deviation, and 10 denotes the smallest. Interpreting the beta and standard deviation sorting criteria as proxies for risk, the first decile can be considered the most risky and the tenth the least. For each decile we present the mean daily return, standard deviation of returns, minimum, maximum, skewness and kurtosis, based on all 9942 observations. The mean daily returns are all fairly close to a tenth of a percent for the beta-sorted deciles, while they are much more dispersed for the standard-deviation-sorted deciles, trending down from about a fifth of a percent to about a twentieth as we move from the most to the least variable return deciles. The standard deviations are in the vicinity of 1 percent. The largest negative daily returns are between about -10 percent and -20 percent, and the largest positive daily returns range up to about 15 percent. The series display varying degrees of skewness and kurtosis with both moments tending to rise in magnitude as we move toward the 10<sup>th</sup> decile of both the beta and standard deviation sorted return deciles.

We plot the unconditional monthly returns for each set of stock deciles in Figures 2 and 3. We focus our attention on the fall and winter, the periods during which the influence of length of night on individuals' moods is well understood by medical professionals. Consider first

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<sup>12</sup>See, for instance, Keim (1983), Reiganum (1983), Roll (1983), and the comprehensive study of seasonality in risk premia on a wide range of assets by Keim and Stambaugh (1986).

Figure 2, returns for the beta-sorted deciles. The stock decile return series all demonstrate a low in September or October, coincident with the point at which mean government bond returns peak in Figure 1. The stock decile returns then reach their peak in January, the time of year when mean bond returns are very nearly at their minimum. Notice that the magnitude of the stock decile returns is roughly proportional to the risk class, with higher risk deciles generally having higher returns than lower risk deciles. (The sole exception is decile 10, corresponding to the lowest beta firms.) Furthermore, the seasonality, low returns in fall and high returns in winter, preserves this ordinal ranking.

While the beta-sorted deciles reflect systematic risk, we can also examine unconditional returns for deciles sorted on the basis of total risk, proxied by standard deviation of returns, as shown in Figure 3. The fall and winter seasonal patterns are very similar to those displayed in Figure 2. The ordinal ranking of returns across standard-deviation-sorted deciles is even cleaner than for beta-sorted deciles: now the pattern is strongly monotonic. Overall, returns are low in the fall and high in the winter for all the deciles, consistent with SAD-influenced investors moving in and out of risky assets in accordance with length-of-day related changes in risk aversion. Of course, these figures represent unconditional results, heavily influenced by some conditional events, such as tax-loss selling.

To further evaluate the prominence of the SAD effect across deciles of different levels of risk, we jointly estimate a set of regressions again making use of Hansen's (1982) GMM and Newey and West (1987) HAC covariance estimates. We expect the magnitude of estimates on the SAD and fall variables to be larger for riskier deciles, consistent with SAD-affected investors' changing tolerance for risk through the fall and winter. The model we estimate is:

$$r_{i,t} = \mu + \rho_{i,1}r_{i,t-1} + \mu_{i,SAD}SAD_t + \mu_{i,Fall}D_t^{Fall} + \mu_{i,Mon}D_t^{Mon} + \mu_{i,Tax}D_t^{Tax} + \epsilon_{i,t} \quad (6)$$

where  $r_{i,t}$  is the trading day  $t$  return for CRSP decile  $i = 1, \dots, 10$ . As before,  $SAD_t$  equals  $H_t - 12$  during fall and winter and equals zero otherwise (where  $H_t$  is the daily number of

hours of night), and  $D_t^{Fall}$  is a dummy variable which equals one when day  $t$  is in the fall and equals zero otherwise.  $D_t^{Mon}$  equals one for the first trading day following a weekend, usually a Monday.  $D_t^{Tax}$  equals one for the last trading day in December and the first five trading days in January.<sup>13</sup> Results based on controlling for autocorrelation in returns using lags of the dependent variable are very similar to results presented below, and are available from the authors on request.

Results of estimating Equation 6 are shown in Table 6, including coefficient estimates, t-tests based on HAC standard errors, the value of  $R^2$  for each estimation, and  $\chi^2$  tests for up to 20 lags (one month) of autocorrelation and ARCH. We find that for all deciles (regardless of sorting criteria), the SAD variable is strongly significantly positive and the fall dummy is strongly significantly negative. Notably, the magnitude of coefficients varies roughly monotonically over the deciles. In the case of beta-sorted deciles, in Panel A, the SAD coefficient is 0.066 for decile 1, and the magnitude of the estimate drops with beta all the way to decile 9. The SAD coefficient estimate for decile 10 is slightly larger than those for deciles 8 and 9. The fall dummy coefficient drops in magnitude from -0.117 for decile 1 to -0.051 for decile 9, rising in magnitude only for decile 10. In the case of volatility-sorted deciles, the coefficient estimates for the SAD and fall variables decline strictly monotonically from decile 1 to 10. The overall pattern displayed by all of these coefficient estimates is consistent with the SAD hypothesis. In the fall, when SAD leads to increased risk aversion for some individuals, investors are relatively more inclined to sell risky deciles of stocks versus less risky deciles. Similarly, after winter solstice when individuals' degree of risk aversion returns to more normal levels, investors are more inclined to purchase risky deciles relative to the less risky deciles, and the return to investors already holding these assets peaks.

At the bottom of Panels A and B we present Wald  $\chi^2$  test statistics, based on the HAC covariance estimates, for testing the joint significance of the SAD and fall variables across deciles. We strongly reject the null of no SAD and fall effect (joint test 1), with a  $\chi^2$  (20

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<sup>13</sup>Keim (1983) and Ritter (1988) suggest the tax-loss selling effect is concentrated in the last trading day of the year and the several trading days in the new year that follow.

degrees of freedom) test statistic of 57 in the case of beta-sorted deciles, and a  $\chi^2$  (20 degrees of freedom) statistic of 81.4 for the standard-deviation-sorted deciles. These results verify that the individually significant SAD and fall coefficient estimates are also jointly significant. The Wald test of the SAD coefficients being the same across deciles (joint test 2) strongly reject this null in favor of the alternative of different coefficient values across deciles, for both the beta- and standard-deviation-sorted deciles. Tests for the fall coefficient value to be the same across deciles (joint test 3) are also strongly rejected for both the beta- and standard-deviation-sorted decile returns. These last two tests indicate that the magnitude of the SAD and fall variables vary significantly according to the risk of a portfolio.

In Table 7 we translate the SAD and fall dummy variable estimates from Table 6 into more easily interpreted terms. Panel A pertains to the beta-sorted data and Panel B contains results for standard-deviation-sorted deciles. For each decile, we present in the first column the total average annualized return. In the next column, we present the average annualized return that is explained by the SAD measure. To obtain this value, we multiply the value of the SAD variable for each month, from Equation 3, by the SAD coefficient estimate from Table 6. We then compound across periods and annualize the result. In the final column of Table 7, we present the average annualized return due to the fall dummy variable for each decile, computed similarly. For each value in Table 7, two and three asterisks denote significance at the 5 percent and 1 percent levels respectively, based on two-sided tests. In the case of the unconditional return column, significance is based on t-tests for a mean daily return different from zero. In the case of the columns for the annualized returns due to the SAD and fall dummy variables, significance is simply carried over from the t-tests on the parameter estimates shown in Table 6.

The results in Table 7 provide some perspective on the economic significance of the impact of SAD across deciles. Notice that in both Panels A and B, the largest annualized return to the SAD variable is observed for decile 1, the decile that contains the highest beta or highest standard deviation stocks, and the return is over 16 percent annually in both

cases. The annual returns drop monotonically through the deciles, with a minor blip upward only in the 10<sup>th</sup> decile for the beta-sorted data, but even at its minimum the return due to SAD is over 2 percent. Similarly, the most extreme annual returns due to the fall dummy are observed for decile 1, roughly -7 percent in Panel A and -12 percent in Panel B. The absolute value of the returns drops monotonically through the deciles, again with a minor blip only in the 10<sup>th</sup> decile for the beta-sorted data. At its minimum absolute value, the return due to the fall dummy is -1 percent. The signs and significance of the annual returns due to the SAD variable and the fall dummy are consistent with SAD-affected investors moving assets out of stocks in the fall and back into stocks after winter solstice, with movements being considerably more aggressive for riskier categories of stocks. The magnitudes of the annual returns due to the SAD and fall variables suggest that the SAD seasonal is economically significant, more prominently in the riskier deciles.

We conducted a variety of robustness checks. Controlling for market risk by including beta, contemporaneous market returns, or lagged market returns as a regressor does not markedly change the sign, significance, or monotonicity of estimates. Similarly, including a lagged dependent variable as a regressor for each of the decile estimations yields results that are virtually identical to those presented above. Detailed results are available from the authors.

## 5 Mutual Fund Flows

The preceding section discussed the seasonal pattern of risk premia in different categorizations of equities. Beyond risk premia, the SAD hypothesis also has implications for the flow of capital between high-risk and low-risk assets. To investigate whether investors adjust the riskiness of their portfolios by shuffling funds between risk classes of assets, we consider mutual fund flows. Mutual funds represent a substantial amount of capital in the United States, according to industry statistics reported in the Investment Company Institute's *Mutual Fund Fact Book* (2002). The combined value of all US mutual funds approached \$7

trillion in 2001. The number of US households owning mutual funds reached almost 55 million that year, representing more than half of all US households, and over 93 million individuals in those households held mutual funds at that time. At the end of 2001, individuals held 76 percent of mutual fund assets, with the remainder held by banks, trusts, and other institutional investors. Furthermore, the majority of individuals who invest in equities hold mutual funds. According to the *Equity Ownership in America* published by the Investment Company Institute and the Security Industry Association (2002), in 2002, 52.7 million (of over 100 million) US households owned some type of equity, 25.4 million owned individual stock, and 47.0 million owned equity mutual funds. The implication is that mutual fund flows reflect the investment decisions of individual investors. That is, if SAD has an influence on individuals' investment decisions, it is reasonable to expect the effects would be apparent in mutual fund flows.

Relative to mutual fund flows, our questions are twofold. First, does the risk aversion that some investors experience with diminished length of day in the fall lead to a shift from risky stock funds into low-risk bond funds? Second, do investors move capital from bond funds back into stock funds after winter solstice, coincident with increasing daylight and diminishing risk aversion?

Various studies have investigated empirical regularities in mutual fund flows. There have been several studies of the causal links between fund flows and past or contemporaneous returns (either of the fund or the market as a whole).<sup>14</sup> Some researchers have looked for fund-specific characteristics that might explain fund flows.<sup>15</sup> A prominent feature of all classes of fund flows is autocorrelation, so following Warther (1995), Remolana, Kleiman,

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<sup>14</sup>Ippolito (1992) and Sirri and Tufano (1998) find that investor capital is attracted to funds that have performed well in the past. Edwards and Zhang (1998) study the causal link between bond and equity fund flows and aggregate bond and stock returns, and the Granger (1969) causality tests they perform indicate that asset returns cause fund flows, but not the reverse. Warther (1995) finds no evidence of a relation between flows and past aggregate market performance, however, he does find that mutual fund flows are correlated with contemporaneous aggregate returns, with stock funds showing correlation with stock returns, bond funds showing correlation with bond returns, and so on.

<sup>15</sup>See for instance Sirri and Tufano (1998), Del Guercio and Tkac (2001), and Bergstresser and Poterba (2002), who variously study the impact on fund flows of fund-specific characteristics including fund age, investment style, and Morningstar rating.

and Gruenstein (1997), and Karceski (2002), among others, we adopt an AR(3) model for fund flows.

The mutual fund flow data we study are determined using data in the CRSP Survivor-Bias Free US Mutual Fund Database. We consider no-load funds which do not penalize investors for deposits or withdrawals.<sup>16</sup> Following Remolana, Kleiman, and Gruenstein (1997), Fortune (1998), Sirri and Tufano (1998), and Gemmill and Thomas (2002), we consider fund flows as a percentage of last period's total net assets. (In aggregating percentage flows across funds, we weight by last period's fund value, analogous to value-weighted stock market returns produced by CRSP.) An alternate method, proposed by Warther (1995), is to divide the fund flows by the prior month's ending dollar value for the entire stock market (NYSE, AMEX, and NASDAQ). As we report below, results are similar using either measure.

The fund flows are computed as a percentage of last period's total net assets as follows:

$$FLOW_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \quad (7)$$

where  $i$  references bond or equity funds,  $TNA_{i,t}$  is the total net asset value of fund  $i$  at the end of period  $t$ , and  $r_{i,t}$  is the return on fund  $i$  over period  $t$ . There is an extensive literature that describes various forms of survivorship bias that can affect mutual fund returns even in the CRSP survivor-bias free data set.<sup>17</sup> To the extent that any of these biases affect fund flows, the impact on bond and equity funds would be similar (biasing both bond and equity fund flows either upward or downward, depending on the specific type of survivorship bias). As we document below, in practice we observe bond and equity fund flows that move in *opposite* directions in the fall and winter, suggesting the influence of SAD on fund flows dramatically dominates any potential influence of survivorship bias.

In order to determine whether there is a SAD-induced seasonal in mutual fund flows,

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<sup>16</sup>No-load funds tend to have relatively larger flows than funds with load fees; see Chordia (1996) and Remolana, Kleiman, and Gruenstein (1997), for instance.

<sup>17</sup>Recent examples of papers studying mutual fund returns survivorship bias include Elton, Gruber, and Blake (2001), Carhart, Carpenter, Lynch, and Musto (2002), and Evans (2003).



we select from the CRSP mutual fund database those funds which are either explicitly risk-seeking in their investment objectives or inherently very safe. Our equity funds include only those which state capital growth as an objective, permit short-selling, invest in unregistered securities, allow borrowing up to 10 percent of the value of the portfolio, or invest at least 25 percent of the fund value in foreign securities. Based on these sorting criteria, we consider an average of 1633 individual equity funds each month (ranging from a minimum of 436 funds to a maximum of 2800). At the end of 2002, the total net asset value of the equity funds we consider was 1.16 trillion dollars. The bond funds we consider are those which invest in corporate bonds rated BBB or better or US government-backed securities (including Ginnie Mae securities). The average number of bond funds in the resulting data set is 1010, with a monthly minimum of 450 and a maximum of 1238. The total net asset value of the bond funds we consider was 810 billion dollars at the end of 2002.<sup>18</sup>

In Table 8 we report summary statistics on the aggregate monthly fund flows for the bond and equity mutual funds. As previously mentioned, fund flows are reported as a percentage of the funds' last period total net assets. The flow data we use span January 1992 through December 2002. The mean monthly equity fund flow is 0.97 percent of the previous period's total equity fund value, while for bond funds the mean flow is 0.56 percent of the last month's bond fund value. The two flow series are similarly variable. The minimum and maximum fund flows are similar across the fund categories at well under 10 percent in a month, and both bond and equity fund flows display little skewness, but equity funds show some leptokurtosis.

In Figure 4 we consider unconditional patterns in mutual fund flows. We plot the deviation of the monthly average percentage flow from the annual average percentage flow for each of equity mutual funds and bond mutual funds. Monthly bond flows, indicated with an asterisk, rise sharply during autumn, peak in December, and then drop sharply in Jan-

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<sup>18</sup>The CRSP codes for the equity mutual funds we consider are AG, GE, GI, IE, and LG, and the codes for the bond funds we use are BQ, GS, GM, MG. CRSP obtains the monthly data from Investment Company Data, Inc., now owned by Micropal.

uary through March. Monthly equity mutual fund flows, marked with solid dots, are below average or declining in the fall and then they rise sharply in January and February. These patterns are consistent with SAD-affected investors shifting their portfolios towards safer assets in the fall, then back into risky assets in the winter.

To more formally investigate seasonal patterns in mutual fund flows, we consider the following model:

$$\begin{aligned}
 FLOW_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,Fall}D_t^{Fall} + \mu_{i,r}r_{i,t-1} \\
 &+ \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t},
 \end{aligned} \tag{8}$$

where  $i$  references bond funds or equity funds,  $FLOW_{i,t}$  is the month  $t$  fund flow expressed as a percentage of last period's total net assets,  $SAD_t$  is the SAD variable as defined in Equation 3,  $D_t^{Fall}$  is the fall dummy variable as defined in Equation 4, and  $r_{i,t-1}$  is the prior month's return to the set of funds (either the stock funds or the bond funds). Consistent with prior studies, we include three lags of the dependent variable to control for autocorrelation. We estimate the models for bond fund flows and equity fund flows jointly in a GMM framework and conduct inference using HAC covariance estimates.

Results of estimating Equation 8 are shown in Table 9. In Panel A of Table 9 we present coefficient estimates, two-sided t-tests based on HAC standard errors, the value of  $R^2$  for each estimation, and Lagrange Multiplier tests for up to 12 lags (a year) of autocorrelation or ARCH. Considering the equity fund flows first, we find that the SAD coefficient estimate is significantly positive and the fall estimate is significantly negative, consistent with risk averse investors shunning risky assets in the fall and then resuming risky holdings as daylight becomes more plentiful. The signs are reversed for the bond fund flows: the SAD coefficient is significantly negative and the estimate on the fall dummy is significantly positive, again consistent with what we expect.

In Panel B we present  $\chi^2$  statistics for testing the joint significance of variables in the bond

and equity fund flow estimations. We strongly reject the hypothesis that the individually significant SAD and fall coefficient estimates are jointly zero. We also strongly reject the hypotheses that the SAD coefficients are equivalent across the bond and equity fund flow estimations and that the fall coefficient estimates are the same across the two cases.

Relative to the average monthly mutual fund flows shown in Table 8 (around 1 percent for equity funds and about half a percent for bond funds), the SAD-related flows (that is, the SAD and fall coefficient estimates from Table 9) are of a comparable magnitude, as large as three quarters of a percent for equity funds and up to almost a full percent for bond funds. In Table 10 we present a detailed analysis of the economic significance of the fund flows due to the SAD and fall variables.

In Panel A of Table 10 we translate the equity mutual fund flows into monetary flows based on the aggregate December 2002 value of all the equity mutual funds we consider, which is 1.16 trillion dollars. The value of the fall dummy in October, 1, multiplied by the fall coefficient estimate, -0.752, yields the first value shown in the top line of the first column. The value indicates that, all else constant, more than three quarters of a percent of the equity mutual funds' value flows out of equity mutual funds on average during October. This represents an outflow exceeding 8 billion dollars, as shown in parentheses in the same cell of the table. The economic impact of the fall variable is the same in each month of the fall, and of course there is no impact in the winter months when the fall dummy equals zero. The economic impact of the SAD variable is shown in the next column. Multiplying the SAD coefficient from Table 9, 0.240, by the value of the SAD variable each month<sup>19</sup> yields the set of figures shown on the left side of the SAD column. For instance, the value of the SAD variable in October, 1.14, times the SAD coefficient of 0.240, equals 0.274. That is, the average inflow of funds that can be attributed to the SAD variable that month, all else constant, is over a quarter a percent of the value of equity funds. This represents more

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<sup>19</sup>The value of the SAD variable, shown in Equation 3, during the fall and winter months is as follows: 1.14 in October, 2.38 in November, 2.94 in December, 2.60 in January, 1.52 in February, and 0.13 in March. This is the median number of hours of night for each month, minus 12.

than three billion dollars, as shown in parentheses. The total *net* effect of the SAD and fall variables is shown in the final column. For instance, the net outflow due to the fall variable in October, -0.752 percent, plus the net inflow due to the SAD variable in October, 0.274 percent, yields a net outflow of -0.478 percent that month, which equates to over five billion dollars net. Notice that the net effect of the fall and SAD variables is negative in all the fall months and positive in all the winter months, consistent with our expectations.

Turning to Panel B, we can analyze the economic magnitude of the bond fund flows, based on the December 2002 aggregate value of 809 billion dollars for the particular bond funds we consider. The fall dummy coefficient estimate of 0.971 translates into over 7 billion dollars in monthly flows into bond funds during October, November, and December. The economic impact of the SAD variable alone varies from under a billion dollars to over five billion dollars in average monthly outflows. The net effect of the fall and SAD variables is positive during the fall months and negative during the winter months, again, consistent with our expectations.

Overall, the evidence suggests that when funds are flowing out of equity funds, they are flowing into bond funds. For instance in October, the SAD/fall-related flow out of equity funds is \$5.55 billion, while the flow into bond funds is \$5.83 billion. Similarly, when funds are flowing into equity funds, they are flowing out of bond funds.

In further robustness checks, we explored the impact of various modifications to the estimation model. We explored both the inclusion of contemporaneous market returns or fund returns as a regressor,<sup>20</sup> the inclusion of lagged market returns as a regressor, and the more parsimonious model excluding any return variable as a regressor, and we found virtually identical results. Warther (1995) found that money market funds, but not other funds, display significant outflows in December and inflows in January. While we don't focus on money market funds, we still investigated whether similar patterns might drive our results for bond and equity fund flows by including December and January dummy variables

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<sup>20</sup>Note that there can be an endogeneity problem in using contemporaneous returns in the regression.

as additional regressors. In all cases, we found standard errors, coefficient estimates, and significance of the SAD and fall variables to be very similar to those we report in this paper. Details on all the robustness checks are available from the authors on request.

## 6 Conclusions

The medical literature is unequivocal that Seasonal Affective Disorder is a serious emotional condition that afflicts millions of people during the seasons when daylight is scarce. The depression associated with SAD in turn affects the willingness to seek sensation, that is, to engage in activities involving risk. It is therefore not surprising that SAD permeates capital markets, which are risky by nature. To date, only the stock market has been studied (KKL 2003) where it has been shown that market indices move with the cycle of light and dark that accompanies the revolution of the Earth around the Sun.

In this paper, we have shown that the seasonal regularities go well beyond equity markets. First, we have documented a cycle in bond returns that is the converse of the SAD stock market return cycle. Just as autumn stock returns tend to drop with increasing length of night, so at the same time bond returns tend to rise. Then as the hours of night cycle moves through its maximum, around December 21, and the days lengthen towards spring, stock returns rise and bond returns drop. These inverted patterns are both statistically and economically significant, and they occur in spite of strong positive correlation between our monthly bond index returns and stock index returns.

Second, this paper has also shown that the cyclical regularities in equities are highest in riskier segments of the stock market. Whether we sort stock portfolios by beta or standard deviation of return, the riskier the decile the higher in almost every instance is the amplitude of the return cycle. This is consistent with SAD-affected investors showing greater aversion to holding risky stocks versus safe stocks in the fall and then showing greater inclination to hold risky stocks versus safe stocks in the new year. Finally, when we examine the movement of funds within the capital market by viewing the flows of money between different classes

of mutual funds during the fall and winter, we find that money moves out of stocks and into bonds in fall as the days shorten. The flow is reversed in the new year as the days lengthen. Not only are the cyclical indicators statistically significant for the flows between different types of funds we consider, even the flows into the safer (riskier) funds correspond closely to the amounts flowing out of the riskier (safer) funds. This is the annual cycle in fund flows that seasonal patterns in daylight and SAD-related risk aversion would suggest.

It should also be recalled that we consider seasonal variation in the willingness to accept risk, not seasonal variation in risk itself. Previous studies of seasonality in risk premia consider patterns, including those around the turn of the year, as being the result of variations in the risk of the securities. For example, Keim and Stambaugh (1986) suggest that risk may drop at the turn of the year, pointing out that de-listings of stocks in the 1927-81 period were most frequent during December and least frequent during January. Indeed, they write on page 359, “The seasonality ... might suggest a tendency for increased risk around the turn of the year.” Of course, it is difficult to distinguish perceptions of risk from willingness to accept risk. Both cause an increase in measured risk premia. It might be argued, however, that if a seasonal influence moves relatively predictably through fall and winter in a pattern that corresponds to the fluctuations in daylight, it is unlikely that smooth variations in *risk* through the course of the year is responsible. Just as SAD is widely accepted as a serious emotional condition that influences the general population, this paper has shown that investors are no different. This should not be a surprise. After all, investors are human.

## References

- Bergstresser, Daniel and James Poterba. Do after-tax returns affect mutual fund inflows? *Journal of Financial Economics*, 2002, 63, 381-414.
- Carhart, Mark M., Jennifer N. Carpenter, Anthony W. Lynch, and David K. Musto. Mutual Fund Survivorship. *Review of Financial Studies*, Winter 2002, 15(5), 1439-1463.
- Carton, Solange, Roland Jouvent, Catherine Bungener, and D. Widlöcher. Sensation Seeking and Depressive Mood. *Personality and Individual Differences*, July 1992, 13(7), 843-849.
- Chang, Eric C. and Roger D. Huang, Time-Varying Return and Risk in the Corporate Bond Market, *Journal of Financial and Quantitative Analysis*, September 1990, 25(3) 323-340.
- Chordia, Tarun. The structure of mutual fund charges. *Journal of Financial Economics*, 1996, 41, 3-39.
- Cohen, Robert M., M. Gross, Thomas E. Nordahl, W.E. Semple, D.A. Oren, and Norman E. Rosenthal. Preliminary Data on the Metabolic Brain Pattern of Patients with Winter Seasonal Affective Disorder. *Archives of General Psychiatry*, July 1992, 49(7), 545-552.
- Del Guercio, Diane, and Paula A. Tkac. The Effect of Morningstar Ratings on Mutual Fund Flows. Mimeo, Federal Reserve Bank of Atlanta, GA, 2001.
- Delgado, Pedro L. Depression: The Case for a Monoamine Deficiency. *Journal of Clinical Psychiatry*, 2000, 61 Suppl. 6, 7-11.
- Edwards, Franklin R. and Xin Zhang. Mutual Funds and Stock and Bond Market Stability. *Journal of Financial Services Research*, 1998, 13(3), 257-282.
- Eisenberg, Amy E., Jonathan Baron, and Martin E.P. Seligman. Individual Differences in Risk Aversion and Anxiety. Mimeo, University of Pennsylvania Department of Psychology, 1998.
- Elton, Edwin J., Martin J. Gruber, and Christopher R. Blake. A First Look at the Accuracy of the CRSP Mutual Fund Database and a Comparison of the CRSP and Morningstar Mutual Fund Databases. *Journal of Finance*, December 2001, 61(6), 257-282.
- Evans, Richard B. Mutual Fund Incubation and Termination: The Endogeneity of Survivorship Bias. Wharton School of Business Manuscript, April 2003.
- Faedda, Gianni L., Leonardo Tondo, M.H. Teicher, Ross J. Baldessarini, H.A. Gelbard, and G.F. Floris. Seasonal Mood Disorders, Patterns in Mania and Depression. *Archives of General Psychiatry*, 1993, 50, 17-23.
- Fama, Eugene F. and Kenneth R. French. The Cross-Section of Expected Returns. *Journal of Finance*, June 1992, 47(2), 427-465.
- Fortune, Peter. Mutual Funds, Part II: Fund Flows and Security Returns. *New England Economic Review*, January/February 1998, 47(2), 3-22.

- Gemmill, Gordon and Dylan C. Thomas. Noise Trading, Costly Arbitrage, and Asset Prices: Evidence from Closed-end Funds. *Journal of Finance*, December 2002, 57(6) 2571-2594.
- Granger, Clive. Investigating Causal Relations by Econometric Models and Cross Spectral Methods. *Econometrica*, April 1969, 37, 424-438.
- Hansen, Lars Peter. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica*, 1982, 50, 1029-1054.
- Harlow, W.V. and Keith C. Brown. Understanding and Assessing Financial Risk Tolerance: A Biological Perspective, *Financial Analysts Journal*, November-December 1990, 50-80.
- Hirschfeld, Robert M.A. History and Evolution of the Monoamine Hypothesis of Depression, *Journal of Clinical Psychiatry*, 2000, 61 Suppl. 6, 4-6.
- Horvath, Paula and Marvin Zuckerman. Sensation Seeking, Risk Appraisal, and Risky Behavior. *Personality and Individual Differences*, January 1993, 14(1), 41-52.
- Investment Company Institute. *Mutual Fund Fact Book: A Guide to Trends and Statistics in the Mutual Fund Industry*, 42nd Edition, 2002.
- Investment Company Institute and the Security Industry Association. *Equity Ownership in America*, 2002.
- Ippolito, Richard A. Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *Journal of Law and Economics*, 1992, 35, 45-70.
- Jordan, Susan D. and Bradford D. Jordan, Seasonality in Daily Bond Returns, *Journal of Financial and Quantitative Analysis*, June 1991, 26(2) 269-285.
- Kamstra, Mark J., Lisa A. Kramer, and Maurice D. Levi, Winter Blues: A SAD Stock Market Cycle, *American Economic Review*, March 2003, 93(1) 324-343.
- Karceski, Jason. Returns-Chasing Behavior, Mutual Funds, and Beta's Death. *Journal of Financial and Quantitative Analysis*, December 2002, 37(4) 559-594.
- Keim, Donald B. Size-related Anomalies and Stock Return Seasonality: Further Empirical Evidence. *Journal of Financial Economics*, June 1983, 12(1), 13-32.
- Keim, Donald B. and Robert F. Stambaugh. Predicting Returns in the Stock and Bond Markets. *Journal of Financial Economics*, December 1986, 17(2), 357-390.
- Kothari, S.P., Jay Shanken, and Richard G. Sloan. Another Look at the Cross-Section of Expected Stock Returns. *Journal of Finance*, March 1995, 50(1), 185-224.
- Lam, Raymond W., Ed., *Seasonal Affective Disorder and Beyond: Light Treatment for SAD and Non-SAD Conditions*, Washington DC: American Psychiatric Press, 1998.
- Molin, Jeanne, Erling Mellerup, Tom Bolwig, Thomas Scheike, and Henrik Dam. The Influence of Climate on Development of Winter Depression. *Journal of Affective Disorders*, April 1996, 37(2-3), 151-155.
- Newey, Whitney K. and Kenneth D. West. A Simple, Positive, Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix, *Econometrica*, 1987, 55, 703-708.



- Reiganum, Marc R. The Anomalous Stock Market Behavior of Small Firms in January. *Journal of Financial Economics*, June 1983, 12(1), 89-104.
- Remolana, Eli M., Paul Kleiman and Debbie Gruenstein. Market Returns and Mutual Fund Flows. *Federal Reserve Bank of New York Economic Policy Review*, July 1997, 33-52.
- Ritter, Jay R. The Buying and Selling Behavior of Individual Investors at the Turn of the Year. *Journal of Finance*, July 1988, 43(3), pp. 701-717.
- Roll, Richard. Was Ist Das? The Turn of the Year Effect and the Return Premia of Small Firms. *Journal of Portfolio Management*, Winter 1983, 9, 18-28.
- Rogalski, Richard J. and Seha M. Tinic. The January Size Effect: Anomaly or Risk Mis-measurement? Mimeo, Dartmouth College, NH, 1984.
- Rosenthal, Norman E. *Winter Blues: Seasonal Affective Disorder: What is It and How to Overcome It*, 2nd Edition. New York: Guilford Press, 1998.
- Schneeweis, Thomas and J. Randall Woolridge. Capital Market Seasonality: The Case of Bond Returns, *Journal of Financial and Quantitative Analysis*, December 1979, 14(5) 939-958.
- Sirri, Erik R. and Peter Tufano. Costly Search and Mutual Fund Flows. *Journal of Finance*, October 1998, 53(5), 1589-1622.
- Telser, Lester G. A Critique of Some Recent Empirical Research on the Explanation of the Term Structure of Interest Rates, *Journal of Political Economy*, August 1967, 75(4), Part 2, 546-561.
- Thaler, Richard H. Anomalies: The January Effect. *Journal of Economic Perspectives*, Summer 1987, 1(1), 197-201.
- Warther, Vincent A. Aggregate mutual fund flows and security returns. *Journal of Financial Economics*, 1995, 39, 209-235.
- Wilson, Jack W. and Charles P. Jones. Is There a January Effect in Corporate Bond and Paper Returns? *Financial Review*, 1990, 25(1) 55-71.
- Wong, Alan and Bernardo Carducci. Sensation Seeking and Financial Risk Taking in Everyday Money Matters. *Journal of Business and Psychology*, Summer 1991, 5(4), 525-530.
- Young, Michael A., Patricia M. Meaden, Louis F. Fogg, Eva A. Cherin, and Charmane I. Eastman. Which Environmental Variables are Related to the Onset of Seasonal Affective Disorder? *Journal of Abnormal Psychology*, November 1997, 106(4), 554-562.
- Zuckerman, Marvin, Monte S. Buchsbaum, and Dennis L. Murphy. Sensation Seeking and its Biological Correlates. *Psychological Bulletin*, January 1980, 88(1), 187-214.
- Zuckerman, Marvin. *Biological Bases of Sensation Seeking, Impulsivity and Anxiety*. Hillsdale, NJ: Lawrence Erlbaum Associates, Inc., 1983.
- Zuckerman, Marvin. Sensation Seeking: A Comparative Approach to a Human Trait. *Behavioral and Brain Science*, 1984, 7, 413-471.

**Table 1: Summary Statistics On Bond Index Percentage Returns**

We present summary statistics on monthly US government bond index returns obtained from CRSP. For each bond index return series we present the number of observations ( $N$ ), mean percentage return (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew) and kurtosis (Kurt). The start and end dates for each series are presented beneath the series names.

Monthly Government Bond Indices Start Date - End Date	$N$	Mean	Std	Min	Max	Skew	Kurt
10 year Govt. Bond Index 1941-05 - 2001-12	728	0.455	1.96	-6.67	10.00	0.682	2.71
7 year Govt. Bond Index 1941-04 - 2001-12	729	0.479	1.64	-7.04	10.75	0.879	5.63
5 year Govt. Bond Index 1941-04 - 2001-12	729	0.470	1.38	-5.80	10.61	0.843	6.65
2 year Govt. Bond Index 1941-01 - 2001-12	732	0.447	0.81	-3.69	8.42	2.070	18.56
1 year Govt. Bond Index 1941-01 - 2001-12	732	0.440	0.53	-1.72	5.61	2.468	16.90

**Table 2: Correlations Between Monthly Bond Indices and Monthly Stock Index**

For various sample periods, we present correlation coefficients based on the covariance between the various monthly US Treasury bond index returns and the monthly CRSP total market stock index returns.  $N$  denotes the number of observations in each sample or sub-sample. The full sample includes data spanning January 1942 through December 2001. Each decade sub-period includes 10 years of monthly data, e.g. January 1950 through December 1959. The only exceptions are the 1940s sub-period, which includes the months January 1942 through December 1949, and the 1990s sub-period, which includes January 1990 through December 2001. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent level respectively, based on two-sided tests.

	10 year Govt. Bond Index	7 year Govt. Bond Index	5 year Govt. Bond Index	2 year Govt. Bond Index	1 year Govt. Bond Index
Full Sample $N = 720$	0.19***	0.17***	0.15***	0.14***	0.11***
1940s $N = 96$	0.13	0.21**	0.12	0.12	0.14
1950s $N = 120$	-0.13	-0.13	-0.20**	-0.11	-0.08
1960s $N = 120$	0.10	0.11	0.11	0.14	0.06
1970s $N = 120$	0.38***	0.34***	0.27***	0.31***	0.31***
1980s $N = 120$	0.25***	0.24***	0.23**	0.18**	0.14
1990s $N = 144$	0.20**	0.15*	0.13	0.07	0.12

**Table 3: Regression Results for  
Monthly Government Bond Index Returns**

We report coefficient estimates from jointly estimating the following expression for each of the monthly government bond indices in a GMM framework:

$$r_{i,t} = \mu_i + \rho_{i,1}r_{i,t-1} + \mu_{i,SAD}SAD_t + \mu_{i,Fall}D_t^{Fall} + \mu_{i,Tax}D_t^{Tax} + \epsilon_{i,t}. \quad (5)$$

Bond index returns ( $r_{i,t}$ , where  $i$  indicates the category of bond maturities) are regressed on a constant ( $\mu$ ), lagged returns, the SAD measure ( $SAD_t = H_t - 12$  during fall and winter, 0 otherwise, where  $H_t =$  median monthly number of hours of night), a dummy for months in the fall ( $D_t^{Fall}$ ), and a tax-loss selling dummy for the month of January ( $D_t^{Tax}$ ).

In Panel A we present parameter estimates, with associated t-statistics below, calculated using Newey and West (1987) HAC standard errors. At the bottom of Panel A, we present the value of  $R^2$  for each index, as well as Lagrange Multiplier  $\chi^2$  test statistics for the presence of up to a year, 12 lags, of autocorrelation (AR) or ARCH. In Panel B we present Wald  $\chi^2$  tests, with degrees of freedom in square brackets, for testing the equivalence of the SAD and fall coefficient estimates to zero. Two and three asterisks denote significance at the 5 percent and 1 percent levels respectively, based on two-sided tests.

**Panel A: Parameter Estimates, T-tests, and Diagnostics**

Parameter	10 year	7 year	5 year	2 year	1 year
$\mu$	0.318*** ( 5.761)	0.356*** ( 7.996)	0.347*** ( 9.728)	0.293*** ( 14.016)	0.239*** ( 16.129)
$\rho_1$	0.096*** ( 6.537)	0.118*** ( 9.415)	0.147*** ( 12.355)	0.261*** ( 22.702)	0.408*** ( 34.881)
$\mu_{SAD}$	-0.181** ( -2.251)	-0.169*** ( -2.693)	-0.158*** ( -3.122)	-0.093*** ( -3.698)	-0.073*** ( -4.978)
$\mu_{Fall}$	0.563*** ( 2.947)	0.541*** ( 3.621)	0.436*** ( 3.484)	0.247*** ( 3.929)	0.175*** ( 4.721)
$\mu_{Tax}$	0.684** ( 2.541)	0.417** ( 2.115)	0.496*** ( 3.061)	0.374*** ( 4.767)	0.286*** ( 6.083)
$R^2$	0.0159	0.0221	0.0287	0.0737	0.1692
AR(12)	17.21	17.78	21.84**	59.82***	128.96***
ARCH(12)	126.28***	101.86***	92.58***	63.89***	85.46***

**Panel B: Joint Test**

Test:	$\chi^2$ [degrees of freedom]
SAD and fall coefficients jointly zero across series	42.4*** [10]

**Table 4: Average Annual Percentage Return  
Due to SAD and Due to Fall Dummy  
for Government Bond Indices**

For each of the monthly government bond series (1, 2, 5, 7, and 10 year maturities, data obtained from CRSP), we report the total average annual percentage return, the average annual percentage return due to the SAD variable, and the average annual percentage return due to the fall variable. In calculating the average annual return due to SAD for a particular index, we take the value of the SAD variable for each month, multiply by the index's SAD variable estimate from Table 3, average across months, and then adjust the outcome to obtain an annualized percentage return. Similarly, in calculating the annual average return due to the fall dummy for a particular index, we take that index's fall dummy variable estimate from Table 3, multiply by the value of the fall dummy variable (one during periods in the fall, zero otherwise), average across months, and then adjust the result to obtain an annualized percentage return. Two and three asterisks denote significance at the 5 percent and 1 percent levels respectively, based on two-sided tests. In the case of the columns for the annualized returns due to the SAD and fall dummy variables, significance is based on t-tests on the parameter estimates from Table 3. In the case of the unconditional return column, significance is based on t-tests for a mean daily return different from zero.

Monthly Government Bond Indices	Total Average Annual Return (%)	Average Annual Return Due to SAD Variable (%)	Average Annual Return Due to Fall Variable (%)
10 year	5.59***	-1.920**	1.700***
7 year	5.89***	-1.800***	1.630***
5 year	5.79***	-1.680***	1.310***
2 year	5.58***	-0.990***	0.740***
1 year	5.49***	-0.780***	0.530***

**Table 5: Summary Statistics on Daily CRSP Decile Returns**

The summary statistics reported in this table are based on beta-sorted CRSP decile returns (Panel A) and volatility-sorted CRSP decile returns (Panel B). The daily data span the period July 3, 1962 through December 31, 2001, for which there are 9942 observations. Decile 1 contains the 10 percent of firms with the largest beta or return standard deviation while decile 10 contains firms with the smallest beta or return standard deviation. For each decile return series we present the mean percentage return (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew) and kurtosis (Kurt).

**Panel A: Beta-Sorted Deciles**

Decile	Mean	Std	Min	Max	Skew	Kurt
1	0.092	1.34	-19.83	14.77	-0.234	11.95
2	0.076	1.10	-17.86	11.82	-0.519	14.52
3	0.079	0.98	-17.35	10.20	-0.707	16.88
4	0.079	0.90	-16.74	11.59	-0.755	21.42
5	0.076	0.82	-14.85	9.96	-0.819	19.92
6	0.078	0.74	-12.88	7.95	-0.788	16.60
7	0.079	0.68	-12.52	9.48	-0.869	23.50
8	0.078	0.60	-11.47	7.35	-1.043	24.27
9	0.077	0.53	-10.06	7.64	-0.838	27.58
10	0.111	0.59	-9.00	8.82	-0.656	24.12

**Panel B: Standard-Deviation-Sorted Deciles**

Decile	Mean	Std	Min	Max	Skew	Kurt
1	0.181	1.18	-14.36	15.00	0.309	13.93
2	0.071	1.06	-15.36	11.96	-0.428	14.86
3	0.062	0.99	-15.74	12.29	-0.589	17.03
4	0.066	0.89	-14.42	9.93	-0.743	17.04
5	0.067	0.81	-13.99	8.90	-0.944	18.65
6	0.064	0.75	-14.49	8.62	-1.119	21.68
7	0.061	0.69	-14.82	8.19	-1.268	29.73
8	0.059	0.62	-14.47	8.34	-1.449	38.94
9	0.054	0.53	-12.98	8.16	-1.492	49.21
10	0.048	0.40	-9.72	5.70	-1.418	46.31

**Table 6: Regression Results for Daily CRSP Decile Returns**

We report coefficient estimates from jointly estimating, in a GMM framework, the following regression using as the dependent variable each of the beta-sorted CRSP decile returns (Panel A) and standard-deviation-sorted CRSP decile returns (Panel B).

$$r_{i,t} = \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,Fall}D_t^{Fall} + \mu_{i,Mon}D_t^{Mon} + \mu_{i,Tax}D_t^{Tax} + \epsilon_{i,t} \quad (6)$$

For each decile  $i = 1, \dots, 10$ , decile returns ( $r_{i,t}$ ) are regressed on a constant ( $\mu$ ); the SAD measure ( $SAD_t = H_t - 12$  during fall and winter, 0 otherwise, where  $H_t =$  number of hours of night); a dummy for trading days in the fall ( $D_t^{Fall}$ ); a dummy for trading days following the weekend ( $D_t^{Mon}$ ); and a dummy for the last trading day of December and the first five trading days of January ( $D_t^{Tax}$ ). Decile 1 contains the 10 percent of firms with the largest beta or return standard deviation while decile 10 contains firms with the smallest beta or standard deviation.

We present parameter estimates, with associated t-statistics in parentheses below, calculated using Newey and West (1987) HAC standard errors. At the bottom of each table, we present the value of  $R^2$  for each estimation, as well as Lagrange Multiplier  $\chi^2$  test statistics for the presence of up to a month, 20 lags, of autocorrelation (AR) or ARCH. We also present Wald  $\chi^2$  tests, with their degrees of freedom in square brackets and their p-values below in parentheses, for testing the equivalence of the SAD and fall coefficient estimates to zero (joint test 1), and for testing the joint equality of the SAD and fall coefficient estimates respectively (joint tests 2 and 3) across the bond return series. Two and three asterisks denote significance at the 5 percent and 1 percent level respectively, based on two-sided tests.

**Panel A: Beta-Sorted CRSP Deciles**

Parameter Estimates, T-tests, and Diagnostics for Deciles 1-5:

Parameter	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5
$\mu$	0.132*** (7.477)	0.112*** (7.699)	0.111*** (8.447)	0.108*** (9.028)	0.106*** (9.616)
$\mu_{SAD}$	0.066*** (4.824)	0.050*** (4.396)	0.048*** (4.811)	0.042*** (4.497)	0.036*** (4.248)
$\mu_{Fall}$	-0.117*** (-3.209)	-0.093*** (-3.059)	-0.091*** (-3.365)	-0.081*** (-3.210)	-0.072*** (-3.191)
$\mu_{Mon}$	-0.301*** (-11.33)	-0.244*** (-11.10)	-0.211*** (-10.69)	-0.189*** (-10.64)	-0.177*** (-10.95)
$\mu_{Tax}$	0.606*** (5.429)	0.473*** (5.216)	0.435*** (5.169)	0.446*** (5.911)	0.421*** (5.785)
$R^2$	0.0201	0.0195	0.0198	0.0209	0.0218
AR(20)	787.80***	840.43***	928.90***	917.46***	989.96***
ARCH(20)	1568.83***	1685.28***	1583.48***	1941.97***	2077.52***

Parameter Estimates, T-tests, and Diagnostics for Deciles 6-10:

Parameter	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
$\mu$	0.105*** (10.368)	0.106*** (11.448)	0.099*** (11.958)	0.099*** (13.985)	0.135*** (18.260)
$\mu_{SAD}$	0.034*** (4.297)	0.032*** (4.493)	0.029*** (4.582)	0.023*** (4.031)	0.030*** (4.884)
$\mu_{Fall}$	-0.075*** (-3.593)	-0.064*** (-3.353)	-0.061*** (-3.556)	-0.051*** (-3.358)	-0.085*** (-5.322)
$\mu_{Mon}$	-0.153*** (-10.51)	-0.161*** (-12.55)	-0.126*** (-10.74)	-0.123*** (-12.43)	-0.136*** (-12.55)
$\mu_{Tax}$	0.422*** (6.075)	0.395*** (6.431)	0.399*** (7.075)	0.422*** (7.979)	0.643*** (11.515)
$R^2$	0.024	0.0275	0.0286	0.0367	0.0552
AR(20)	1141.30***	1123.32***	1259.01***	1295.11***	803.43***
ARCH(20)	1890.03***	2711.30***	2689.15***	2748.64***	3227.79***

Joint Tests

Test:	$\chi^2$ [degrees of freedom]
(1) SAD and fall coefficients jointly zero across deciles	57.0*** [20]
(2) SAD coefficients equivalent across deciles	27.6*** [9]
(3) Fall coefficients equivalent across series	24.5*** [9]



**Panel B: Standard-Deviation-Sorted CRSP Deciles**

Parameter Estimates, T-tests, and Diagnostics for Deciles 1-5:

Parameter	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5
$\mu$	0.215*** (14.886)	0.122*** (9.099)	0.106*** (8.360)	0.104*** (9.016)	0.098*** (9.031)
$\mu_{SAD}$	0.074*** (5.944)	0.051*** (4.609)	0.049*** (4.776)	0.045*** (4.865)	0.042*** (4.906)
$\mu_{Fall}$	-0.207*** (-6.500)	-0.142*** (-4.948)	-0.115*** (-4.233)	-0.104*** (-4.239)	-0.088*** (-3.861)
$\mu_{Mon}$	-0.369*** (-17.16)	-0.309*** (-15.20)	-0.249*** (-13.09)	-0.211*** (-12.18)	-0.175*** (-10.99)
$\mu_{Tax}$	1.364*** (10.052)	0.718*** (7.337)	0.454*** (5.444)	0.341*** (4.438)	0.256*** (3.828)
$R^2$	0.0802	0.0411	0.027	0.0228	0.0183
AR(20)	1058.98***	939.12***	926.60***	1009.34***	1123.12***
ARCH(20)	2051.47***	2117.56***	2465.95***	2335.15***	2292.26***

Parameter Estimates, T-tests, and Diagnostics for Deciles 6-10:

Parameter	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
$\mu$	0.093*** (9.201)	0.085*** (9.269)	0.081*** (9.669)	0.071*** (10.053)	0.059*** (10.620)
$\mu_{SAD}$	0.036*** (4.535)	0.030*** (4.117)	0.023*** (3.623)	0.017*** (3.073)	0.009** (2.118)
$\mu_{Fall}$	-0.076*** (-3.635)	-0.059*** (-3.074)	-0.049*** (-2.837)	-0.031** (-2.107)	-0.016 (-1.396)
$\mu_{Mon}$	-0.147*** (-9.893)	-0.122*** (-8.951)	-0.104*** (-8.528)	-0.087*** (-8.600)	-0.059*** (-7.789)
$\mu_{Tax}$	0.191*** (3.092)	0.163*** (2.834)	0.122** (2.376)	0.136*** (3.032)	0.147*** (4.183)
$R^2$	0.0148	0.0121	0.0104	0.0114	0.0126
AR(20)	1106.09***	1118.05***	1116.94***	1250.94***	1577.62***
ARCH(20)	1811.10***	1498.09***	1635.72***	1682.51***	1208.69***

Joint Tests

Test:	$\chi^2$ [degrees of freedom]
(1) SAD and fall coefficients jointly zero across deciles	81.4*** [20]
(2) SAD coefficients equivalent across deciles	51.0*** [9]
(3) Fall coefficients equivalent across series	57.9*** [9]

**Table 7: Average Annual Percentage Return  
Due to SAD and Due to Fall Dummy  
for CRSP Deciles**

We consider CRSP deciles sorted by beta in Panel A and sorted by return standard deviation in Panel B. Decile 1 contains the 10 percent of firms with the largest beta or return standard deviation while decile 10 contains firms with the smallest beta or standard deviation. In calculating the average annual percentage return due to SAD for a particular decile, we take the value of the SAD variable on each trading day, multiply by that decile's SAD variable estimate (from Table 6), average across days, then adjust the value to obtain an annualized percentage return. Similarly, in calculating the annual average percentage return due to the fall dummy for a particular decile, we determine that decile's fall dummy variable estimate (from Table 6) multiply by the value of the fall dummy variable for each day (one during the fall, zero otherwise), average across days, and annualize the result. Two and three asterisks denote significance at the 5 percent and 1 percent level respectively, based on two-sided tests.

**Panel A: Beta-Sorted CRSP Deciles**

Decile	Total Average	Average	Average
	Annual	Annual Return	Annual Return
	Return (%)	Due to	Due to
		SAD Variable (%)	Fall Variable (%)
1	25.71***	16.310***	-7.140***
2	20.67***	12.050***	-5.670***
3	21.55***	11.730***	-5.590***
4	21.55***	10.070***	-4.990***
5	20.87***	8.650***	-4.470***
6	21.34***	8.010***	-4.630***
7	21.77***	7.570***	-3.950***
8	21.55***	6.920***	-3.760***
9	21.05***	5.380***	-3.190***
10	31.77***	7.050***	-5.220***

**Panel B: Standard-Deviation-Sorted CRSP Deciles**

Decile	Total Average	Average	Average
	Annual	Annual Return	Annual Return
	Return (%)	Due to	Due to
		SAD Variable (%)	Fall Variable (%)
1	56.86***	18.580***	-12.22***
2	19.39***	12.380***	-8.590***
3	16.66***	11.850***	-6.980***
4	17.7***	10.950***	-6.360***
5	18.11***	10.120***	-5.380***
6	17.14***	8.600***	-4.700***
7	16.46***	7.030***	-3.650***
8	15.89***	5.490***	-3.030***
9	14.44***	3.920***	-1.920**
10	12.61***	2.120**	-1.000*

**Table 8: Summary Statistics on Percentage Mutual Fund Flows**

We present summary statistics on monthly mutual fund flows for a total of 132 months using data provided by CRSP. The CRSP codes for the equity mutual funds we consider are AG, GE, GI, IE, and LG, and the codes for the bond funds we use are BQ, GS, GM, MG. The flows are computed as  $FLOW_{i,t} = \frac{TNA_{i,t} - (1+r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}$ , where the  $i$  index references bond or equity funds,  $TNA_{i,t}$  is the total net asset value of fund  $i$  at the end of period  $t$ , and  $r_{i,t-1}$  is the return on fund  $i$  over period  $t$ . For each set of fund flows we present the number of monthly observations (N), the mean monthly flow (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew) and kurtosis (Kurt). Details on the number of individual funds available in these categories each month are as follows: for equity funds the minimum is 436, the maximum is 2800, and the mean is 1633; for bond funds the minimum is 450, the maximum is 1238, and the mean is 1010.

Mutual Fund Data Set Start Date - End Date	N	Mean	Std	Min	Max	Skew	Kurt
Equity 1992-01-31 - 2002-12-31	132	0.972	1.06	-4.54	5.83	-0.081	7.61
Bonds 1992-01-31 - 2002-12-31	132	0.557	1.44	-3.33	6.47	0.316	1.99

**Table 9: Regression Results for Mutual Fund Flows**

We report coefficient estimates from jointly estimating the following regression for each of the types of mutual funds in a GMM framework:

$$FLOW_{i,t} = \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,Fall}D_t^{Fall} + \mu_{i,r}r_{i,t-1} + \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t} \quad (7)$$

The monthly flows are computed as  $FLOW_{i,t} = \frac{TNA_{i,t} - (1+r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}$ , where the  $i$  index references bond or equity funds,  $TNA_{i,t}$  is the total net asset value of fund  $i$  at the end of month  $t$ , and  $r_{i,t-1}$  is the return on fund  $i$  over month  $t$ . Flows are regressed on the SAD measure ( $SAD_t = H_t - 12$  during fall and winter, 0 otherwise, where  $H_t =$  number of hours of night), a dummy for months in the fall ( $D_t^{Fall}$ ), the lagged fund return, and three lags of the dependent variable.

In Panel A we present coefficient estimates with HAC robust t-tests in parentheses. At the bottom of Panel A we present the value of  $R^2$  for each estimation, as well as Lagrange Multiplier  $\chi^2$  test statistics for the presence of up to a year, 12 lags, of autocorrelation (AR) or ARCH. In Panel B we present Wald  $\chi^2$  tests, with their degrees of freedom in square brackets and their p-values below in parentheses, for testing the joint equality of SAD and fall coefficient estimates across the bond and equity estimations. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent level respectively, based on two-sided tests.

**Panel A: Parameter Estimates, T-tests, and Diagnostics**

Parameter	Equity	Bonds
$\mu$	0.277*** ( 3.073)	0.138 ( 1.147)
$\mu_{SAD}$	0.240*** ( 3.006)	-0.219** ( -2.173)
$\mu_{Fall}$	-0.752*** ( -5.166)	0.971*** ( 4.162)
$\mu_r$	0.006 ( 0.407)	0.275* ( 1.802)
$\rho_1$	0.137* ( 1.895)	0.044 ( 0.577)
$\rho_2$	0.259*** ( 6.681)	0.081 ( 1.285)
$\rho_3$	0.210*** ( 4.614)	0.352*** ( 8.425)
$R^2$	0.1997	0.2412
AR(12)	21.73**	9.77
ARCH(12)	34.62***	13.13

**Panel B: Joint Tests**

Test:	$\chi^2$ [degrees of freedom]
SAD and Fall coefficients jointly zero	43.2*** [4]
SAD coefficients equivalent	10.4*** [1]
Fall coefficients equivalent	37.5*** [1]

**Table 10: Economic Magnitude of Mutual Fund Flows  
based on Coefficient Estimates from Table 9**

We translate the SAD and fall coefficient estimates from Table 9 into economically meaningful values based on the December 2002 aggregate value of the equity mutual funds we consider (\$1.16 trillion) and the bond mutual funds we consider (\$809 billion). The first value presented in each cell is the percentage mutual fund flow that can be attributed to the variable(s) specified in the column header, and the second value in each cell, in parentheses, is the economic equivalent of the percentage flow in reference to the aggregate value of the funds we consider. Panel A reports equity mutual fund flows and bond funds flows are shown in Panel B.

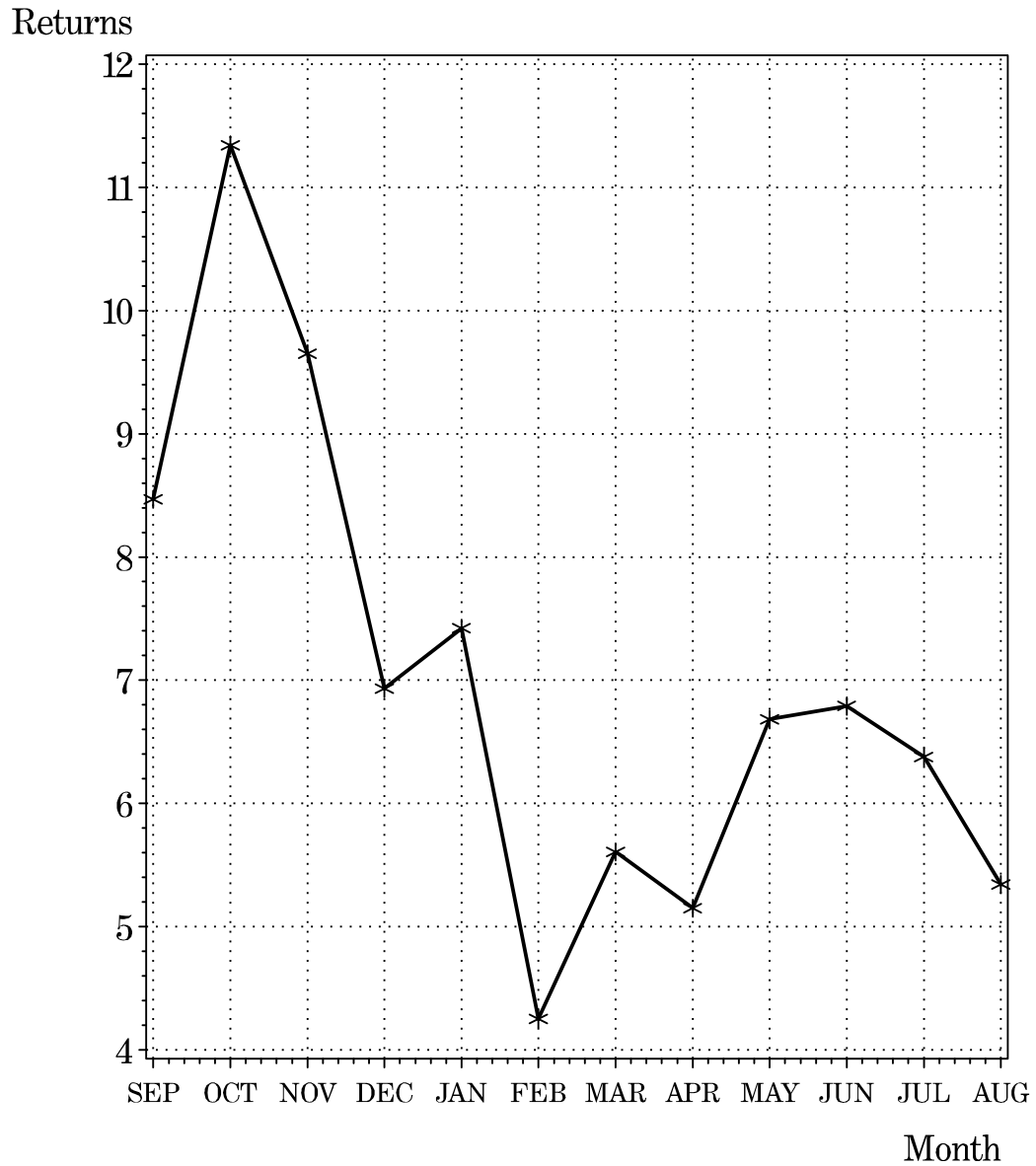
**Panel A: Equity Mutual Fund Flows:**

Month	Marginal Effect of Fall Variable: % Flows (\$ Flows)	Marginal Effect of SAD Variable: % Flows (\$ Flows)	Total Net Effect of Both Fall and SAD Variables: % Flows (\$ Flows)
October	-0.752 (-\$8.72 billion)	0.274 (\$3.17 billion)	-0.478 (-\$5.55 billion)
November	-0.752 (-\$8.72 billion)	0.571 (\$6.63 billion)	-0.181 (-\$2.10 billion)
December	-0.752 (-\$8.72 billion)	0.706 (\$8.18 billion)	-0.046 (-\$0.53 billion)
January	0 (\$0)	0.624 (\$7.24 billion)	0.624 (\$7.24 billion)
February	0 (\$0)	0.365 (\$4.24 billion)	0.365 (\$4.24 billion)
March	0 (\$0)	0.031 (\$0.36 billion)	0.031 (\$0.36 billion)

**Panel B: Bond Mutual Fund Flows**

Month	Marginal Effect of Fall Variable: % Flows (\$ Flows)	Marginal Effect of SAD Variable: % Flows (\$ Flows)	Total Net Effect of Both Fall and SAD Variables: % Flows (\$ Flows)
October	0.971 (\$7.86 billion)	-0.250 (-\$2.02 billion)	0.721 (\$5.83 billion)
November	0.971 (\$7.86 billion)	-0.521 (-\$4.22 billion)	0.450 (\$3.64 billion)
December	0.971 (\$7.86 billion)	-0.644 (-\$5.21 billion)	0.327 (\$2.65 billion)
January	0 (\$0)	-0.570 (-\$4.61 billion)	-0.570 (-\$4.61 billion)
February	0 (\$0)	-0.333 (-\$2.69 billion)	-0.333 (-\$2.69 billion)
March	0 (\$0)	-0.028 (-\$0.23 billion)	-0.028 (-\$0.23 billion)

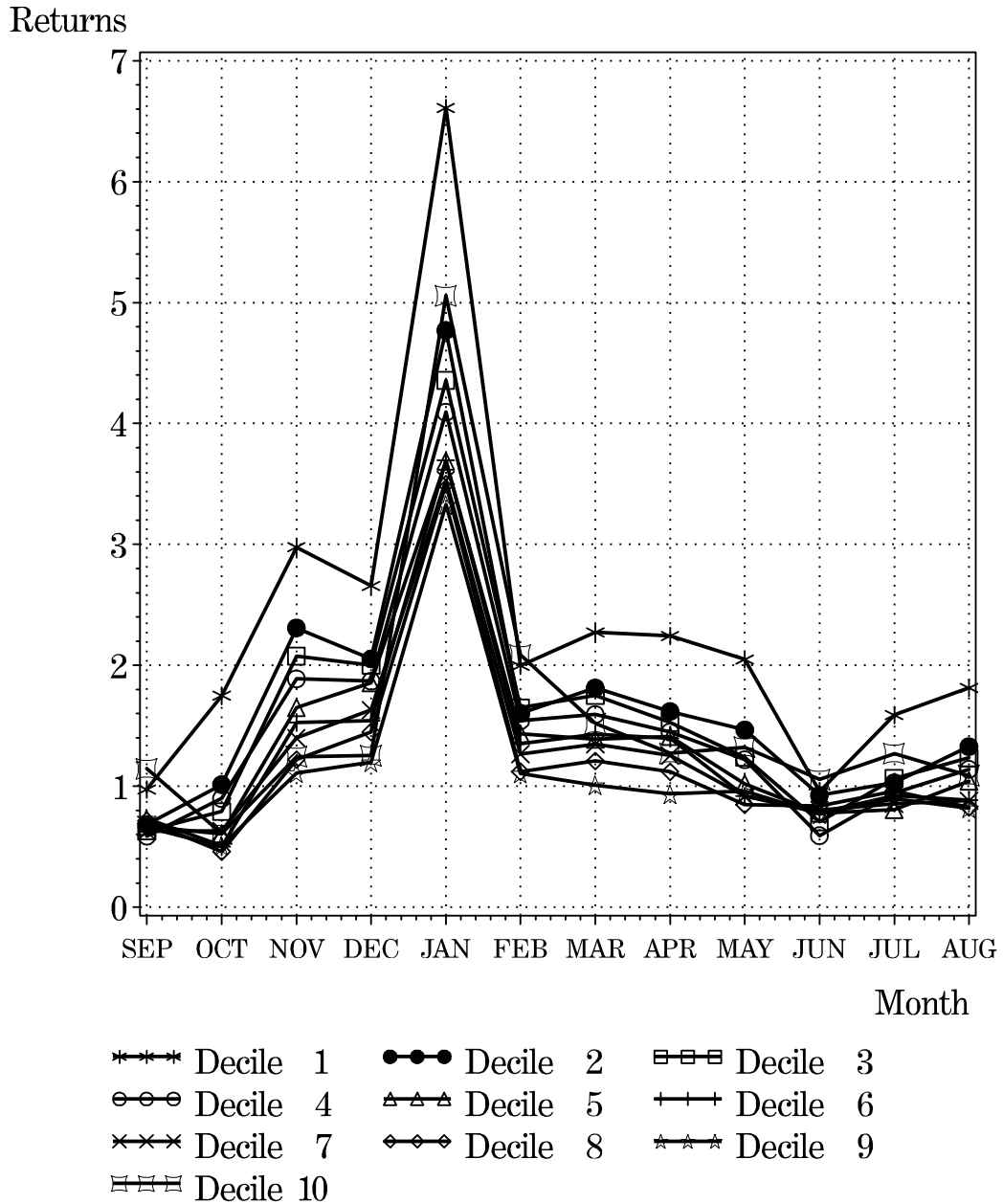
Figure 1:  
Average Percentage Monthly Bond Returns



\*\*\* Average Bond Return

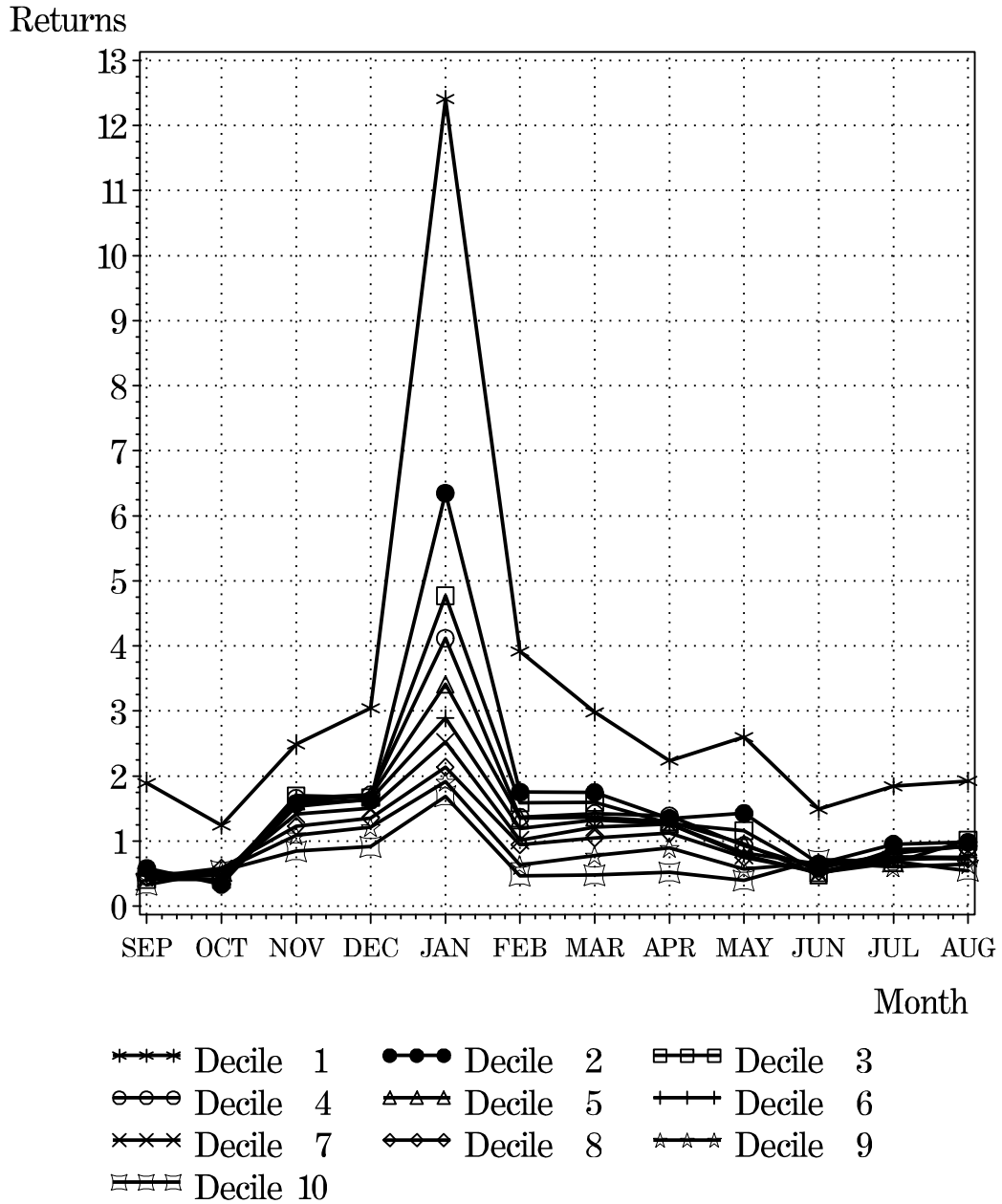
We plot average monthly bond returns, expressed on an annualized basis, based on the 1, 2, 5, 7, and 10 year bond indices. The averages are computed on the full range of CRSP data available: January 1941 through December 2001 for the 1, 2, and 5 year series; April 1941 through December 2001 for the 5 and 7 year series; and May 1941 to December 2001 for the 10 year series.

Figure 2:  
Average Percentage Monthly Stock Decile Returns  
Beta Sorted



We plot average monthly stock decile returns, expressed on an annualized basis, for CRSP deciles sorted on the basis of beta. The averages are computed on the full range of data available, July 3, 1962 through December 31, 2001. Decile 1 contains the 10 percent of firms with the largest beta while Decile 10 contains the 10 percent of firms with the smallest beta.

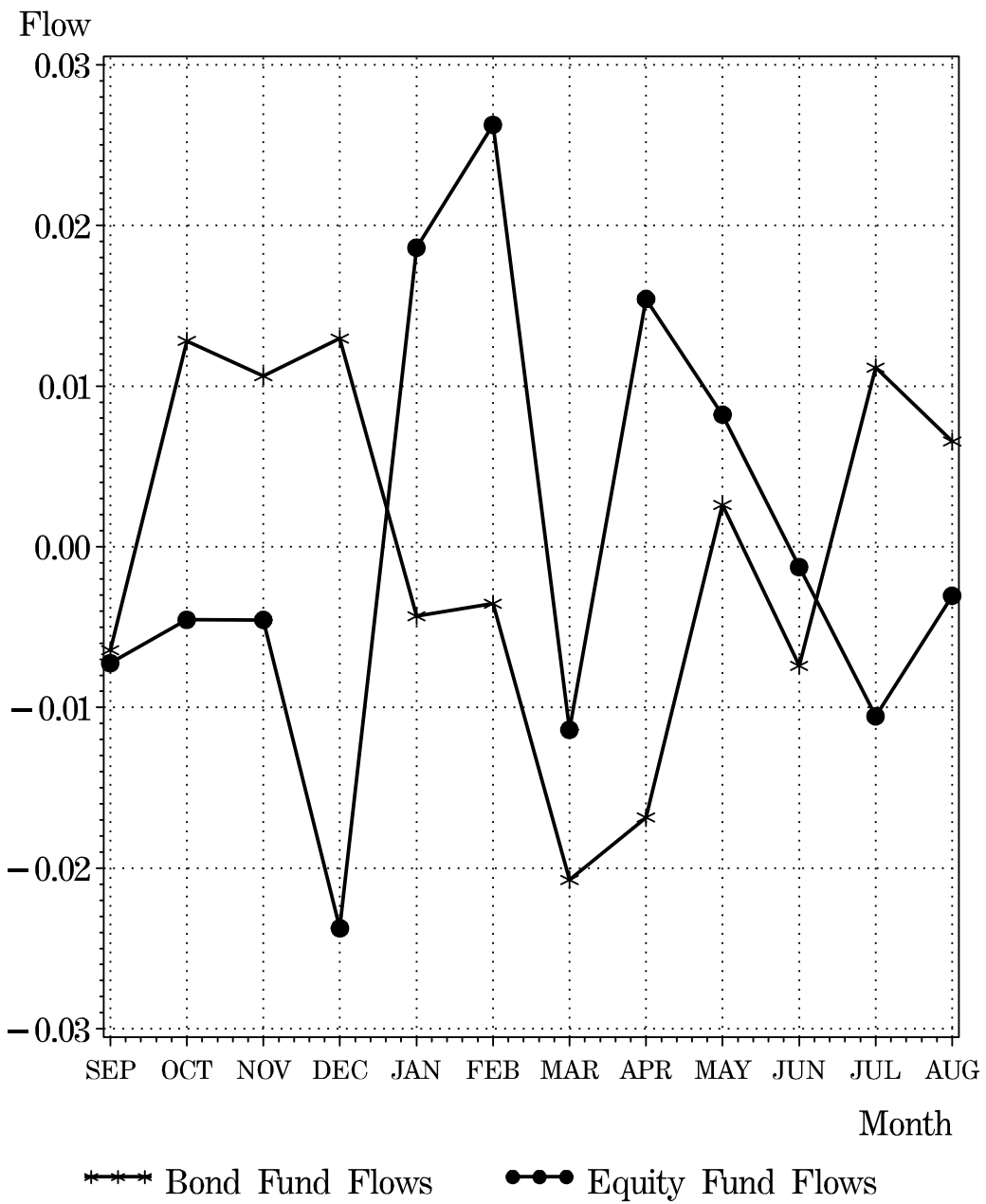
Figure 3:  
Average Percentage Monthly Stock Decile Returns  
Standard Deviation Sorted



We plot average monthly stock decile returns, expressed on an annualized basis, for CRSP deciles sorted on the basis of return standard deviation. The averages are computed on the full range of data available, July 3, 1962 through December 31, 2001. Decile 1 contains the 10 percent of firms with the largest standard deviation of returns while Decile 10 contains the 10 percent of firms with the smallest standard deviation.



Figure 4:  
 Average Monthly Equity and Bond Fund Flows  
 Percentage of Last Period Total Market Value, Deviation From Mean



We plot deviations of average monthly flows from average annual flows for bond mutual funds and equity mutual funds. The flows upon which the averages are based are computed as a percentage of the prior period's aggregate market value for the appropriate fund. We use data for 132 equity funds and 136 bond funds provided by CRSP over January 1992 through December 2002.