Seasonal Asset Allocation: Evidence from Mutual Fund Flows

Abstract

Investment managers and finance researchers alike are interested in the flow of investments into and out of mutual funds. Fund managers have a financial incentive to attract capital under their management, while academic researchers are interested in mutual fund flows partly due to their fascination with the relationship between fund flows and fund performance. In light of the interest, we closely examine the determinants of fund flows, revealing a substantial regularity in mutual fund investment patterns that has previously gone unnoticed: seasonally varying flows between funds of different risk characteristics. The seasonality in flows is shown to be consistent with the influence of seasonal affective disorder, SAD, on investor sentiment. According to extensive clinical research on SAD, many millions of people suffer from depression or "winter blues" when the hours of daylight shrink in the fall, and recover as the days lengthen in the winter. Furthermore, experimental evidence shows that depression is in turn associated with increased risk aversion. This SAD / risk aversion linkage implies *movements* of funds from riskier to safer investments as risk aversion rises in the fall, and from safer to riskier investments as risk aversion subsides in the winter. This paper examines seasonality in the movement of investment dollars into and out of both risky equity mutual funds and safe bond mutual funds to see if they correspond to the implications of SAD. We find economically and statistically significant seasonal patterns in mutual fund flows consistent with the SAD hypothesis, and we find that modeling the SAD-related seasonal adds considerably to our ability to explain flows. Overall, this provides powerful non-return-based evidence of the importance of SAD for seasonality in financial markets in general, and potentially for helping to explain fund return persistence in particular. Further, the results have implications for the timing of advertisements by the mutual fund industry which spends over half a billion dollars each year encouraging investors to purchase mutual funds.

The mutual fund industry spends more than half a billion dollars a year advertising to attract investment inflows. (See Pozen, 2002.) The benefits to attracting capital are clear: a conservative estimate of the management fees collected by mutual funds in the United States in 2003 is 50 billion dollars on close to 7.5 trillion dollars under management.[1] Jain and Wu (2000) demonstrate that advertised funds attract significantly more new investments than the average fund. Gallaher, Kaniel, and Starks (2004) show that advertising is significantly related to fund family flows. Given the formidable magnitudes of advertising budgets and the even grander scale of the management fees they seek to attract, it is conceivable that if fund managers had access to more information about determinants of flows of mutual fund investment, they would be keen to use it to tailor their promotion efforts.

Among academics, interest in mutual fund flows extends beyond the influence of advertising. For instance, in a growing literature, researchers have documented a relationship between mutual fund flows and subsequent mutual fund performance. Gruber (1996) and Zheng (1999) find that funds with recent inflows subsequently perform better than those with recent outflows. Wermers (2003) demonstrates this phenomenon, known as the smart money effect, may arise because money that flows into the hands of managers of a fund that has performed well is often used to purchase more well-performing stocks (which are themselves persistent), leading to further good performance for the fund. Given the evidence that performance may depend on prior flows, it is essential to understand the determinants of fund flows to fully understand the predictability of fund performance.

In light of the commercial and academic interest in the flow of capital into and out of mutual funds, in this study we dig deeply into the determinants of mutual fund flows themselves. Prior research has found fund flows are partly explained by past or contemporaneous returns (either returns to the fund or returns to the market as a whole). See, for instance, Ippolito (1992) and Sirri and Tufano (1998). Some studies, including Del Guercio and Tkac

[1]According to the Investment Company Institute (2003), the average expense ratio charged across 46 large equity mutual funds is 0.7 percent, while according to the Securities and Exchange Commission (2000), the average may be closer to 1 percent across all funds.

(2001) and Bergstresser and Poterba (2002), have found various fund-specific characteristics help explain fund flows. Further, many researchers have noticed that a prominent feature of all classes of fund flows is persistence, as documented by Warther (1995), Karceski (2002), and others.

We examine the possibility of a regularity in mutual fund flows that has gone hitherto unnoticed. The motivation for the regularity is based on work by Kamstra, Kramer, and Levi (2003, 2004) demonstrating novel seasonal patterns in returns to publicly traded stocks and bonds that are economically and statistically significant, and very robust. As we discuss in detail below, if KKL's rationale for the seasonal patterns in stock and bond returns is valid, we should observe seasonal patterns in the flow of funds between stock and bond mutual funds that correspond to those documented in this paper.

KKL suggest the pattern they find in stock and bond returns arises as a consequence of seasonal depression among investors. Medical evidence firmly demonstrates that as the number of hours of daylight drops in the fall, about ten percent of the population becomes depressed with a condition known as seasonal affective disorder, or SAD.[2] It has further been shown that depression leads to risk averse behavior, both in general and in the context of making financial decisions in particular.[3] Given the links between seasonal cycles in daylight, depression, and risk aversion, it is conceivable that with the reduction of daylight in the fall, SAD-affected investors sell risky stocks and buy safer assets like bonds. When daylight becomes more abundant in the new year and SAD-influenced investors begin reverting to normal levels of risk aversion, those investors would then sell bonds and resume risky holdings. KKL (2003) and Garrett, Kamstra, and Kramer (2004) find evidence consistent with this hypothesis in international stock market returns, and KKL (2004) find support in US Treasury bond returns, even after controlling for established market seasonalities such as tax- loss selling. On average, stock market returns are lowest and bond returns are high-

[2]The nature, incidence, and cause of SAD are discussed in a wide range of articles in the medical and psychology literatures well surveyed by Lee et. al. (1998).

[3]Examples include Harlow and Brown (1990) and Wong and Carducci (1991).

est during the fall months when the number of hours of daylight is falling toward its annual minimum. Mean stock returns are then highest and bond returns lowest as daylight becomes more plentiful through winter. That is, stock and bond returns display reverse seasonal patterns, something that is difficult to explain without seasonal variations in risk aversion. We expect fund flows to exhibit similar seasonality, with opposing flows of investment into and out of mutual funds at opposite extremes of the risk spectrum as investors act on seasonal changes in their risk aversion.

In this paper we consider whether there is evidence from mutual fund flows to support the SAD hypothesis. By studying flow of funds instead of asset returns, we examine a set of data unrelated to KKL's prior findings. In particular, we consider whether there are seasonal regularities in the flow of investments into and out of safe and risky mutual funds that are consistent with the SAD-based argument and with previously documented seasonal patterns in stock and bond returns. We hypothesize that capital is flowing out of risky equity mutual funds and into safe bond mutual funds when reduced daylight leads to higher levels of risk aversion for some investors, and that capital is flowing out of bond funds and back into stock funds when daylight becomes more abundant. We find evidence supporting such flows, reinforcing the importance of seasonal depression and hence time-varying risk aversion in determining individuals' portfolio choices and for financial markets in general.

The remainder of the paper is organized as follows. In Section 1, we describe seasonal affective disorder and explain how it can translate into an economically significant influence on a SAD-affected investor's choice of assets. In Section 2, we briefly define the measures we use to capture the impact of SAD on investment decisions. In Section 3 we present evidence that the flow of capital into and out of mutual funds follows a seasonal pattern consistent with SAD. We provide a broad range of robustness checks in Section 4. Section 5 concludes.

1 The Link between Daylight and Risk Aversion

The link between daylight and investment choices is based on two elements. First, seasonal variation in daylight results in depression during the fall and winter among a sizable segment of the population. Second, depression is associated with increased risk aversion. Both of these connections are based on widely accepted behavioral and biochemical evidence. Further, they have been extensively studied in both clinical and experimental studies.

As for the first element of the link between daylight and risk aversion, namely the causal connection between hours of daylight and seasonal depression, evidence has been documented in many studies, including Molin et. al. (1996) and Young et. al (1997). Over the last couple of decades, a large industry has emerged informing people how to deal with the disorder, and offering products that create "natural" light to help sufferers cope with symptoms.[4] According to Rosenthal (1998), about ten percent of the American population begins to suffer the depressive effects of SAD or winter blues during the fall, recovering in the new year as the days lengthen. Other researchers have documented similar proportions around the world. The evidence on and interest in SAD make it clear that the condition is a very real and pervasive problem.

Regarding the second element of the link between daylight and risk aversion mentioned above, there is substantial clinical evidence on the negative influence depression has on individuals' risk-taking behavior. Psychologists measure risk inclination using a scale they call "sensation seeking." (One who seeks risk would obtain a high score on sensation seeking scales, while someone who is risk averse would score low.) Many studies in psychology have sought to determine whether depressed individuals are more or less likely to expose themselves to risk, and there is strong evidence that depressed people take fewer chances. That is, depression is associated with a low sensation seeking tendency.[5]

[4]Examples of popular books by leading SAD researchers that are devoted to approaches for dealing with SAD are Rosenthal (1998) and Lam (1998).

[5]Evidence supporting the tendency for depression to lead to reduced sensation seeking includes Zuckerman (1980, 1983, 1984), Carton et. al. (1992), and Eisenberg, Baron, and Seligman (1998). A book by Zuckerman (1994) provides an excellent survey of the voluminous sensation seeking literature.

Papers exploring sensation seeking / risk inclination among individuals in *financial* contexts include Sciortino, Huston, and Spencer (1987), Harlow and Brown (1990), Wong and Carducci (1991), and Horvath and Zuckerman (1993). Harlow and Brown document the connection between sensation seeking and financial risk tolerance in an experimental setting involving a first price sealed bid auction. They find that one's willingness to accept financial risk is significantly related to sensation seeking score and to blood level of neurochemicals associated with sensation seeking.[6] In another experimental study, Sciortino, Huston, and Spencer (1987) use a panel study of 85 participants to examine the precautionary demand for money. They show that after controlling for various relevant factors such as income and wealth, those individuals who score low on sensation seeking scales (i.e., those who are risk averse) hold larger cash balances, about a third more than the average person, to meet unforeseen future expenditures. Further evidence in the financial realm is provided by Wong and Carducci (1991) who show that people with low sensation seeking scores display greater risk aversion in making financial decisions, including decisions to purchase stocks, bonds, and automobile insurance. Additionally, Horvath and Zuckerman (1993) studied about a thousand individuals in total, and found that sensation seeking scores were significantly positively correlated with the tendency to take financial risks. Together, the evidence on lack of daylight leading to SAD, SAD leading to depression, and depression leading to risk aversion give us reason to consider whether daylight influences choices between alternative investments of different risk and hence the dollar flows between assets of differing risk.

2 Measuring SAD

Since the impact of SAD worsens as the number of hours of daylight decreases (or equivalently, as the number of hours of night increases), and since the seasonal cycle in hours of daylight varies by latitude, we define our SAD measure based on New York's latitude, 41

[6] See Zuckerman (1983, 1994) for details on the biochemistry of depression and sensation seeking.

degrees north.[7] In principle, one could use any latitude in the Northern Hemisphere, since all locations in a given hemisphere follow the same cycle in the length of the day, differing only in amplitude.[8]

Evidence in the medical and psychology literatures suggests that depression and other symptoms of SAD occur in the fall and winter, with symptoms starting as early as autumn equinox and persisting as late as spring equinox for some individuals. Thus our SAD measure takes on non-zero values in the fall and winter only.[9] Defining H_t as the number of hours of night, SAD_t measures the length of night in fall and winter relative to the annual average number of hours of night, 12:[10]

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

SAD_t equals zero at the fall equinox and spring equinox, and takes on positive values (equal to the number of hours of night in excess of 12) throughout the fall and winter months. Consistent with the view that investors become increasingly risk averse in the fall, we should observe investment funds accumulating in bond funds and leaving stock funds in the fall. On the other hand, we should observe investment funds exiting bond funds and accumulating in stock funds in the new year as risk aversion returns to normal with the lengthening of the day. The SAD measure is symmetric around winter solstice, December 21, being the same for a given number days prior to the longest night of the year as for the same number of days that follow. This feature of the SAD variable prevents it from capturing the pattern we

[7]Studies that find prevalence of SAD correlates with latitude include Lingjaerde et. al. (1986), Potkin et. al. (1986), and Rosen et. al. (1990).

[8]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 *number of hours of direct sunshine* (which depends on the presence of cloud cover). They find that additionally controlling for hours of sunshine does not materially change the sign or significance of SAD-related variables or any other variables in their regressions.

[9]We set the fall to start on September 21 and the winter to end on March 20, the equinoxes. When working with monthly data, as we do here, we set the fall to start with October and winter to end with March.

[10]Note that defining the SAD measure in terms of hours of night versus hours of daylight leaves inference unchanged, affecting only the sign of coefficient estimates on SAD-related variables.

expect to see: opposing flows across the fall and winter seasons. Therefore, we additionally use a dummy variable for the fall:[11]

$$D_t^{FALL} = \begin{cases} 1 & \text{for trading days in the fall} \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

This dummy variable allows but does not require the impact of SAD on flows to differ across the fall and winter seasons. The effect of the fall variable is to shift the mean during the fall (September 21 to December 20, the onset period of SAD) relative to the winter (December 21 to March 20, the period of recovery from SAD), allowing asymmetry in flows across these two seasons, consistent with what we expect.

3 Seasonality in Mutual Fund Flows

While prior work has studied the influence of SAD on asset returns, the SAD hypothesis also has implications for the flow of capital between different classes of assets. Thus we investigate whether investors adjust the riskiness of their portfolios by shuffling funds between risk classes of assets. According to the Investment Company Institute and the Security Industry Association (2002), 52.7 million (of over 100 million) US households owned some type of equity in 2002, 25.4 million owned individual stock, and 47.0 million owned equity mutual funds. According to the Investment Company Institute (2002), individuals held 76 percent of mutual fund assets at the end of 2001, with the remainder held by banks, trusts, and other institutional investors. The implication of all these statistics is that mutual fund flows predominantly 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.[12]

[11] 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.

[12] In general, there must be an investor on the other side of every purchase or sale of bonds or equities, with the possible exception of purchases (sales) by fund holders for which the fund manager simply builds up (draws down) cash reserves. Implicit in our argument that the effects of SAD would show up in mutual fund flows is the assumption that risk averse investors, in particular those predisposed to SAD, prefer investments in mutual funds over direct investment in securities that underlie mutual funds.

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).[13] Some researchers have looked for fund-specific characteristics that might explain fund flows.[14] A prominent feature of all classes of fund flows is autocorrelation, so following Warther (1995), Remolona, Kleiman, 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 from the CRSP Survivor-Bias Free US Mutual Fund Database. We consider no-load funds which do not penalize investors for deposits or withdrawals.[15] Following Remolona, 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, our results are similar using either measure.

[13]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 fund flows showing correlation with stock returns, bond fund flows showing correlation with bond returns, and so on.

[14]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.

[15]No-load funds tend to have relatively larger flows than funds with load fees; see Chordia (1996) and Remolona, Kleiman, and Gruenstein (1997), for instance.

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

$$FLOW_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}, \tag{3}$$

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.[16] To the extent that any of these biases affect fund flows, the impact on bond and equity funds would be in the same direction (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 conditional 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, 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 new or unregistered securities, allow borrowing over 10 percent of the value of the portfolio, permit a portfolio turnover rate over 100 percent per year, 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

[16] 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).

810 billion dollars at the end of 2002.[17]

In Table 1 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 0.972 percent of the previous period's total equity fund value, while for bond funds the mean flow is 0.557 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, although equity funds show some leptokurtosis.

In Figure 1 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. Thus values above zero represent above average flows and values below zero correspond to below average flows. We focus our attention on months in the fall and winter, the seasons during which there is theoretical motivation for and clinical evidence of SAD having an impact on human sentiment. Monthly bond flows, indicated with an asterisk, are well above average in the autumn months (October, November, and December), and then drop sharply in the new year, reaching their minimum in March, the last month of winter. Monthly equity mutual fund flows, marked with solid dots, are below average and declining in the fall months, and then they rise sharply in January, remaining above average for the rest of winter. These patterns are consistent with SAD-affected investors shifting their portfolios towards safer assets in the fall, then towards risky assets in the winter.[18]

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

[17]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.

[18]Figure 1 uses fund flows as a percentage of the value of the equity or bond funds. We also computed the flows as a percentage of *all* mutual funds in the CRSP database and found the resulting plot, available from the authors on request, to be qualitatively identical.

following model,

$$\begin{aligned} \text{Model 1:} \quad FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D_t^{FALL} + \mu_{r_{i,t-1}} r_{i,t-1} \\ &+ \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t}, \end{aligned}$$

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 1, D_t^{FALL} is the fall dummy variable as defined in Equation 2, 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 previous studies, we include three lags of the dependent variable to control for autocorrelation. (Note that while Jain and Wu (2000) show that a fund having advertised is a significant determinant of inflows to that particular fund and Gallaher, Kaniel, and Starks (2004) show that advertising is related to fund family flows, we do not control for advertising in our analysis of *aggregate* flows. Certainly it is true that at least some of the funds we consider are advertising at any point in time. Since Jain and Wu show that past performance is an excellent indicator of current advertising expenditure, our inclusion of past fund returns should instrument for any aggregate impact of advertising in our sample.) We estimate the models for bond fund flows and equity fund flows jointly in a GMM framework. Results of estimating Model 1 are shown in Table 2.

In Panel A we present coefficient estimates and two-sided t-tests based on Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. The SAD and fall coefficient estimates are shown in bold. Considering the equity fund flows first, we find that the SAD 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.[19]

[19]Since we claim that SAD-affected investors alter their portfolios seasonally on the basis of the *riskiness*

In Panel B we present several diagnostic statistics. First, the value of adjusted R^2 is provided for each estimation. By comparing the adjusted R^2 values to those that arise from estimating a model that differs from Model 1 only in its exclusion of the SAD_t and D_t^{FALL} variables, we can evaluate whether controlling for the influence of SAD meaningfully contributes to our ability to explain flows. In unreported results, we find that estimating Model 1 without SAD_t and D_t^{FALL} yields an adjusted R^2 of 0.091 for equities and 0.148 for bonds. The values in Table 2 based on the model that includes SAD_t and D_t^{FALL} are 0.159 for equities and 0.202 for bonds. The fact that the explanatory power has risen by at least a third in both cases suggests our ability to understand capital flows is enhanced by modeling the SAD effect. Next in Panel B we provide an F-test on the joint significance of the regression (labeled Test B1) and a χ^2 statistic for testing the null that the SAD and fall variables are jointly zero (labeled Test B2). Based on Test B1 we conclude that the variables in Model 1 are strongly jointly significant, and based on Test B2 we strongly reject the null that the SAD and fall variables are jointly zero. Finally in Panel B we present Lagrange Multiplier test statistics for up to 12 lags, i.e. a year, of autocorrelation or ARCH. Our use of HAC standard errors is justified by the mostly significant evidence of ARCH, a commonly observed feature of financial data.[20]

In Panel C of Table 2 we present χ^2 statistics to investigate the possibility that the individually significant coefficient estimates from Panel A are jointly insignificant across the bond and equity estimations, perhaps due to spurious correlations with other variables in the model. P-values are shown below the test statistics in parentheses. We strongly reject

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of the underlying securities, we verified that the bond mutual funds we study are considerably safer than the equity mutual funds in terms of conventional risk measures. Indeed, the beta of the bond fund returns is 0.006 versus a beta of 0.97 for the equity fund returns. Furthermore, the bond fund returns are an order of magnitude less volatile than the equity fund returns.

[20]Significant evidence of autocorrelation is absent for the bond flow data, but appears for most model specifications of equity flows, at the 5% or 10% level of significance. As lags of the dependent variable are instruments in our GMM estimation, parameter estimate inconsistency can result if residual autocorrelation is in fact a feature of the data or model and not just an artifact of the particular period of data we work with. To guard against this possibility, we also estimated augmented models that remove all significant evidence of autocorrelation. These augmented models yielded little or no change in our results. In the interest of brevity we omit the results of the augmented models and report only the results based on the model specification typically adopted in the literature (with three lags of the dependent variable).

Test C1, the hypothesis that the individually significant SAD and fall coefficient estimates are jointly zero across the bond and equity fund estimations. We also strongly reject Test C2, that the SAD coefficients are equivalent across the bond and equity fund estimations, and Test C3, that the fall coefficient estimates are the same across the two cases. Overall, we can safely assume that the individually significant coefficients in Panel A maintain their joint significance across the bond and equity estimations.

Relative to the average monthly mutual fund flows shown in Table 1 (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 2) 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 3 we present a detailed analysis of the economic significance of the flows due to the SAD and fall variables.

In Panel A of Table 3 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 2, 0.240, by the value of the SAD variable each month yields the set of figures shown on the left side of the SAD column.[21] For instance, the value of the SAD variable in October, 1.14, times the SAD coefficient of 0.240, equals 0.274. That

[21] The value of the SAD variable, shown in Equation 1, 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.

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 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 dollars, while the flow into bond funds is 5.83 billion dollars. Similarly, in months when funds are flowing into equity funds, they are flowing out of bond funds.

4 Robustness of Results

In this section we discuss the robustness of our results to various modifications of Model 1 estimated in the previous section. We vary components of that model one at a time, and later two at a time, to see whether the sign and significance of the SAD and fall variables are affected.

Some studies of mutual fund flows, including Remolona, Kleiman, and Gruenstein (1997) and Fortune (1998), have used past *market* returns instead of past mutual fund returns to explain flows. In Model 2, we replace Model 1's lagged fund return regressor with the lagged market return (defined as r^M_{t-1}, using the total return on NYSE, AMEX, and NASDAQ reported by CRSP).

$$\begin{aligned} \text{Model 2:} \quad FLOW_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,FALL}D_t^{FALL} + \mu_{r^M_{t-1}}\mathbf{r^M_{t-1}} \\ &+ \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Studies including Warther (1995) and Remolona, Kleiman, and Gruenstein (1997), examine the relationship between fund flows and contemporaneous returns. Thus, in Model 3 we replace the lagged returns regressor with an instrument for contemporaneous fund returns, $\hat{r}_{i,t}$, and in Model 4 we replace the lagged returns regressor with an instrument for contemporaneous market returns, $\hat{r}^M_{i,t}$. (To avoid endogeneity problems that arise from regressing flows on simultaneously determined returns, we do not use actual contemporaneous returns as a regressor in Models 3 and 4. Instead take the forecasted returns obtained from a regression of returns on three lags of returns, with the forecasts denoted $\hat{r}_{i,t}$ and $\hat{r}^M_{i,t}$, and we use them as instruments for contemporaneous returns in Models 3 and 4.)

$$\begin{aligned} \text{Model 3:} \quad FLOW_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,FALL}D_t^{FALL} + \mu_{r_{i,t}}\mathbf{\hat{r}_{i,t}} \\ &+ \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

$$\begin{aligned} \text{Model 4:} \quad FLOW_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,FALL}D_t^{FALL} + \mu_{r^M_t}\ \mathbf{\hat{r}^M_t} \\ &+ \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 5 excludes returns altogether from the set of regressors.

$$\begin{aligned} \text{Model 5:} \quad FLOW_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,FALL}D_t^{FALL} \\ &+ \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Warther (1995) finds that money market funds display significant outflows in December and inflows in January. While we don't focus exclusively on money market funds in this study, we are obliged to investigate whether similar patterns might drive our results for bond and equity fund flows by including December and January dummy variables as additional regressors. If Warther's findings for money market funds extend more generally, we may observe flows out of bond funds (and perhaps into equity funds in December) and flows into bond funds (and perhaps out of equity funds) in January. Thus, Model 6 is exactly like Model 1 plus two additional regressors: D_t^{DEC} is a dummy variable that equals one for the month of December and zero otherwise, and D_t^{JAN} is a dummy variable that equals one for the month of January and zero otherwise.

Model 6:

$$\begin{aligned} FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D_t^{FALL} + \mu_{r_{i,t-1}} r_{i,t-1} + \mu_{i,DEC} \mathbf{D_t^{DEC}} \\ &+ \mu_{i,JAN} \mathbf{D_t^{JAN}} + \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

To explore the possibility that the seasonality in flows we attribute to SAD is actually driven by end-of-year distributions of equity fund capital gains being parked in bond funds for a period of time by some investors, we estimate Model 7. In this model we replace the fall dummy variable with dummies for each of the months in the fall (October, November, and December), plus we incorporate the January dummy to simultaneously allow for the possibility of January inflows which Warther (1995) documents in money market funds.

Model 7:

$$\begin{aligned} FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{r_{i,t-1}} r_{i,t-1} + \mu_{i,OCT} \mathbf{D_t^{OCT}} + \mu_{i,NOV} \mathbf{D_t^{NOV}} + \mu_{i,DEC} \mathbf{D_t^{DEC}} \\ &+ \mu_{i,JAN} \mathbf{D_t^{JAN}} + \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

We report results from estimating each of these regression models in Table 4. As before, each model is composed of a pair of regressions, one for equity flows and another for bond flows. This pair of regression equations is estimated jointly using GMM as in the previous section, allowing joint hypothesis tests on the significance of the SAD and fall coefficients and of the differences between these coefficients across the bond and equity asset classes.

Panel A of Table 4 contains parameter estimates with HAC two-sided t-statistics in parentheses. Parameter estimates for the SAD and fall variables are shown in bold. We see that for all the models, μ_{SAD} and μ_{FALL} maintain their expected signs: μ_{SAD} is consistently negative for equity funds and positive for bond funds, and μ_{FALL} is everywhere positive for equities and negative for bonds. All of the estimates are roughly the same order of magnitude relative to the values obtained for Model 1 (shown in Table 2), suggesting the economic impact of the SAD effect is robust to the alternate model specifications we explore. In spite of including dummy variables for up to four of the six months during which SAD_t is working, the magnitude of the SAD estimates for Models 6 and 7 has *risen* for both equity and bond funds relative to estimates in Table 2 and relative to other models shown in Table 4. Further, the SAD and fall estimates are almost everywhere significant.[22]

Panel B contains diagnostic statistics. The value of adjusted R^2 for each regression has everywhere risen relative to the value of adjusted R^2 that arises in estimating Model 1 without SAD_t and D_t^{FALL}, suggesting SAD_t and D_t^{FALL} contribute remarkably to our ability to explain flows.[23] Test B1, the F-test on the joint significance of the regression, is everywhere significant at the 1 percent level or better, and Test B2 everywhere strongly rejects the null that the SAD and fall coefficient estimates are jointly zero (note Test B2 is undefined for Model 7).

Panel C contains χ^2 test statistics for several joint tests. Notice that for all of the cases in Table 4 where the tests are defined, we continue to reject at the five percent level or better the following: Test C1 that the SAD and fall coefficient estimates are jointly zero across the equity and bond estimations for a given model, Test C2 that the SAD estimates are equal

[22] The only two instances where the SAD estimate is not significant at the ten percent level (for bond funds under the specifications of Models 6 and 7) are cases where the use of extra monthly dummy variables leads to multicollinearity and hence reduced power. We note the sign and magnitude are unchanged; only the standard error has increased, leading to insignificant tests, which is classic evidence of multicollinearity.

[23] Recall that for the estimation of Model 1 excluding SAD_t and D_t^{FALL} as regressors led to adjusted R^2 values of 0.091 for equities and 0.148 for bonds.

across bond and equity funds for a given model, and Test C3 that the fall estimates are equal across bond and equity funds for a given model.

Note that results for the October, November, December, and January dummy variables in Models 6 and/or 7 do not detract support from the SAD hypothesis. Recall that we included two extra monthly dummies in Model 6 because Warther (1995) found evidence of flows out of money market funds in December and flows into money market funds in January. If Warther's findings for money market funds extend to our bond funds (which include money market funds as well as other types of safe assets), we would expect flows out of bond funds in December (and possibly into equity funds) and flows into bond funds in January (and possibly out of equity funds). We actually find the reverse pattern in our data: the December dummy coefficient estimates for Model 6 suggest funds are flowing out of equity funds in December and into bond funds. There are no significant flows into or out of either equities or bonds in January, aside from what the SAD variable itself picks up. In Model 7, we included four extra monthly dummies to allow for the possibility that year-end capital gains in equity funds are placed in bond funds for a period by some investors. We do see evidence consistent with such distributions in October, November, and December (though the evidence is indistinguishable from the SAD hypothesis itself, since the October, November, and December dummies are now picking up what was previously measured by the fall dummy variable). However, in spite of the fact that we are using dummy variables for four of the six months the SAD coefficient maintains its magnitude and expected sign.

Until this point, our dependent variable has been monthly flows defined as a proportion of the value of the funds themselves, $FLOW_{i,t} = \frac{TNA_{i,t}-(1+r_{i,t})TNA_{i,t-1}}{TNA_{i,t-1}}$. For the next set of robustness checks we adopt an alternate definition employed in the literature (see Warther, 1995, for instance), flows defined as a proportion of the total market capitalization:

$$FLOW^*_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{MKT_{t-1}}. \tag{4}$$

As before, i references bond or equity funds, $TNA_{i,t}$ is the total net asset value of fund i at the end of month t, and $r_{i,t}$ is the return on fund i over period t. Now MKT_{t-1} is the total market capitalization at time $t-1$, based on NYSE, AMEX, and NASDAQ, as provided by CRSP.

We re-estimate Model 1 using the new definition of fund flows as the dependent variable. The new model is called Model 1*.

$$\begin{aligned}\text{Model 1*:} \quad FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,FALL}D^{FALL}_t + \mu_{r_{i,t-1}}r_{i,t-1} \\ &+ \rho_{i,1}FLOW^*_{i,t-1} + \rho_{i,2}FLOW^*_{i,t-2} + \rho_{i,3}FLOW^*_{i,t-3} + \epsilon_{i,t}\end{aligned}$$

We also re-estimate Models 2-7 with the new dependent variable. Results appear in Table 5. Panel A contains coefficient estimates and HAC robust t-statistics (two-sided). Once again, the SAD and fall coefficient estimates appear in bold. Magnitudes have dropped by roughly an order of magnitude simply because the dependent variable is now expressed as a proportion of a much larger number (the value of the total stock market versus what we previously used, the value of the equity or bond funds being considered). The signs of the SAD estimates are unchanged, taking on positive values for equity funds and negative values for bond funds. These estimates are significant in the majority of cases. The fall coefficients are correctly signed and always significant: negative for equities and positive for bonds. The results for Models 6 and 7 in Table 5 mirror what was presented for these models in Table 4. The joint tests shown in Panel C uniformly reject all three null hypotheses that the SAD and fall coefficient estimates are jointly zero within each model, and that the SAD or fall estimates are equivalent across the bond and equity funds within each model.

Panel B contains the value of adjusted R^2 for each estimation, an F-test on the joint significance of the regression (Test B1), a χ^2 statistic for testing the null that the SAD and fall coefficient estimates are jointly zero (Test B2), and χ^2 test statistics for autocorrelation and ARCH. Results are similar to those shown in previous tables. The adjusted R^2 values in Table 5 can be compared to the adjusted R^2 values that emerge from the unreported estimation of Model 1* without using the SAD_t and D^{FALL}_t variables as regressors: 0.010 for equities and 0.214 for bonds. In each case, including SAD_t and D^{FALL}_t yields a considerably higher value of adjusted R^2, suggesting, as before, that our ability to explain flows is enhanced by modeling the potential influence of time-varying risk aversion due to seasonal depression. Panel C contains Wald χ^2 statistics for our three sets of joint tests across the bond and equity estimations, Tests C1 - C3. In all cases where the tests are defined, we strongly reject the null, as before.

To sum up, there appears to be strong support for the existence of a strong seasonal in fund flows, consistent with SAD-influenced investors moving funds between asset classes as their preferences for risk time-vary, and consistent with seasonal movements in returns documented by KKL (2003, 2004) and Garrett, Kamstra, and Kramer (2004). Our results are invariant to the inclusion/exclusion of fund returns and market returns as regressors, both lagged and contemporaneous. Our findings are robust to including both December and January dummy variables, as well as to simultaneously including dummies for each of October, November, December, and January (which is striking, given these specifications dummy out up to four of the six months for which we aim to explain fund flow seasonality). Even modifying the way we define fund flows leaves the qualitative nature of the results unchanged.

When the SAD and fall coefficient estimates shown in Tables 4 and 5 for Models 1 - 7 are converted into monthly net dollar flows (analogous to Table 3), we consistently observe total net outflows for equities and inflows for bonds in the fall when days are shortening and the incidence of SAD is increasing. Likewise, we consistently observe total net inflows for equities and outflows for bonds in the winter as days lengthen and as SAD subsides. In the interest of brevity, we omit the detailed monthly net dollar flows based on the robustness results, though they are available from the authors on request.

5 Conclusions

Seasonal Affective Disorder is a serious medical condition that afflicts millions of people during the seasons when daylight is scarce. The depression associated with SAD in turn adversely affects the willingness of influenced investors to engage in activities involving risk. It is therefore not surprising that SAD affects choices made by investors in capital markets. Studies done to date have found economically and statistically significant evidence of a systematic influence on stock and bond returns related to seasonal cycles in daylight and depression. In this paper, we have documented a cycle in mutual fund investment flows consistent with the implications of SAD.

By examining the movement of capital into and out of mutual funds at opposing ends of the risk spectrum during the fall and winter, we find that money moves out of stock funds and into bond funds in fall as the days shorten. The flow is reversed in the new year as the days lengthen. The seasonal flows are statistically significant and quantitatively large, representing billions of dollars. The cycle in fund flows is consistent with seasonal patterns in daylight and risk aversion affecting portfolio allocation decisions among SAD-influenced investors. It would be difficult to explain the observed opposing flows between stock and bond funds without seasonal variation in risk aversion. Our confidence in the relevance of SAD is increased by learning that returns (that is, price-based data) and funds flow (that is, quantity-based data) confirm the same seasonality predicted by the impact of the condition on risk aversion.

The findings add to our understanding of investor behavior, suggesting that the mutual fund industry, which spends in total more than half a billion dollars per year on advertising, would be well-advised to time their promotion efforts to the seasons. The most fruitful ad campaign may be one that aggressively pushes safe classes of funds in the fall when many investors are more risk averse than usual and then promotes riskier funds through the winter and into spring when risk aversion is reverting to normal levels. The findings also contribute to our appreciation of the determinants of flows of capital into and out of mutual funds. Given prior research has established close links between fund flows and fund performance, a natural next step would be to explore the extent to which SAD-linked flows explain subsequent fund performance. This is left for future research.

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Table 1: Summary Statistics on Monthly 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 2: 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:

$$\begin{aligned}\text{Model 1:}\quad FLOW_{i,t} &= \mu_i + \mu_{i,SAD}SAD_t + \mu_{i,FALL}D_t^{FALL} + \mu_{r_{i,t-1}}r_{i,t-1} \\ &+ \rho_{i,1}FLOW_{i,t-1} + \rho_{i,2}FLOW_{i,t-2} + \rho_{i,3}FLOW_{i,t-3} + \epsilon_{i,t}\end{aligned}$$

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. In Panel B we present the value of adjusted R^2 for each estimation, an F-test on the joint significance of the regression (labeled Test B1), a χ^2 statistic (with 2 degrees of freedom) for the null that the SAD and fall coefficient estimates are jointly zero (Test B2), and Lagrange Multiplier χ^2 test statistics for the presence of up to 12 lags of autocorrelation (AR) or ARCH (both with 12 degrees of freedom). In Panel C we present Wald χ^2 tests, with p-values below in parentheses, for the following: Test C1 is to see whether the SAD and fall variable coefficients are jointly zero across the bond and equity mutual funds for a given model, Test C2 is to determine whether the SAD coefficients are the same across the bond and equity funds for a given model, and Test C3 tests whether the fall coefficients are the same across the bond and equity funds for a given model. Tests C1, C2, and C3 have 4, 1, and 1 degree of freedom respectively. 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

(HAC Robust T-Statistics)

Parameter	Equity	Bonds
μ	0.277***	0.138
	(3.073)	(1.147)
μ_{SAD}	**0.240*****	**-0.219****
	(3.006)	(-2.173)
μ_{FALL}	**-0.752*****	**0.971*****
	(-5.166)	(4.162)
$\mu_{r_{t-1}}$	0.006	0.275*
	(0.407)	(1.802)
ρ_1	0.137*	0.044
	(1.895)	(0.577)
ρ_2	0.259***	0.081
	(6.681)	(1.285)
ρ_3	0.210***	0.352***
	(4.614)	(8.425)

Panel B: Diagnostics

Adj. R^2	0.159	0.202
Test B1: Significance of the Regression	147.6***	138.6***
Test B2: SAD & Fall estimates jointly zero within fund type	27.0***	18.3***
AR	23.3**	10.2
ARCH	34.6***	13.1

Panel C: Joint χ^2 Tests

(P-Values)

Test C1: SAD & Fall estimates jointly zero across fund types	43.2***
	(0.0000)
Test C2: SAD estimates equal across fund types	10.4***
	(0.0013)
Test C3: Fall estimates equal across fund types	37.5***
	(0.0001)

Table 3: Economic Magnitude of Mutual Fund Flows based on Coefficient Estimates from Table 2

We translate the SAD and fall coefficient estimates from Table 2 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)

Table 4: Robustness Checks with Fund Flows Expressed as a Percentage of Net Asset Value

We explore, one-by-one, modifications of the regression model estimated in Table 2, Model 1. In each case, the change in the model specification relative to Model 1 is indicated in the model name, with any variable added to the model itself shown in bold.

Model 2: Lagged market return used as a regressor

$$\begin{aligned} FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D_t^{FALL} + \mu_{r^M_{t-1}} \mathbf{r^M_{t-1}} \\ &+ \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 3: Contemporaneous fund return used as a regressor (using instrumental variables)

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

Model 4: Contemporaneous market return used as a regressor (using instrumental variables)

$$\begin{aligned} FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D_t^{FALL} + \mu_{r^M_t} \mathbf{\hat{r}^M_t} \\ &+ \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 5: No market return regressor included

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

Model 6: January and December dummy variables used as regressors

$$\begin{aligned} FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D_t^{FALL} + \mu_{r_{i,t-1}} r_{i,t-1} + \mu_{i,DEC} \mathbf{D_t^{DEC}} \\ &+ \mu_{i,JAN} \mathbf{D_t^{JAN}} + \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 7: October, November, December and January dummies used as regressors; no fall dummy included

$$\begin{aligned} FLOW_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{r_{i,t-1}} r_{i,t-1} + \mu_{i,OCT} \mathbf{D_t^{OCT}} + \mu_{i,NOV} \mathbf{D_t^{NOV}} + \mu_{i,DEC} \mathbf{D_t^{DEC}} \\ &+ \mu_{i,JAN} \mathbf{D_t^{JAN}} + \rho_{i,1} FLOW_{i,t-1} + \rho_{i,2} FLOW_{i,t-2} + \rho_{i,3} FLOW_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

We report coefficient estimates from estimating each of these regression models (jointly for bond mutual funds and equity mutual funds for each model specification) in a GMM framework. 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 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.

$r_{i,t-1}$ and $r_{i,t}$ represent lagged and contemporaneous equity or bond fund returns, and r^M_{t-1} and r^M_t represent lagged and contemporaneous market returns. (To avoid problems introduced by using contemporaneous returns as a regressor in estimating our models, we use instrumental variables to generate predicted values, $\hat{r}^M_t$ or $\hat{r}_{i,t}$, and use the predicted values as a regressor in our model instead of the contemporaneous returns.) In all models, 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) and three lags of the dependent variable. In all but Model 7, a fall dummy variable is used as a regressor (D_t^{FALL} equals 1 during October, November, and December, and zero otherwise).

In Panel A we present coefficient estimates with HAC robust t-tests in parentheses. In Panel B we present the value of adjusted R^2 for each estimation, an F-test on the joint significance of the regression (labeled Test B1), a χ^2 statistic (with 2 degrees of freedom) for the null that the SAD and fall coefficient estimates are jointly zero (Test B2), and Lagrange Multiplier χ^2 test statistics for the presence of up to 12 lags of autocorrelation (AR) or ARCH (both with 12 degrees of freedom). In Panel C we present Wald χ^2 tests, with p-values below in parentheses, for the following: Test C1 tests the null that the SAD and fall variable coefficients are jointly zero across the bond and equity mutual funds for a given model, Test C2 tests the null the SAD coefficients are the same across the bond and equity funds for a given model, and Test C3 tests the null that the fall coefficients are the same across the bond and equity funds for a given model. Tests C1, C2, and C3 have 4, 1, and 1 degree of freedom respectively. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent level respectively, based on two-sided tests.

Table 5: Robustness Checks with Fund Flows Expressed as a Percentage of Lagged Total Market Capitalization

We explore modifications of the regression model estimated in Table 2, Model 1. The first change, affecting all models estimated in the table, is to the dependent variable. While Table 4 examined flows as a percentage of total net asset value of the fund, in this table we examine flows as a percentage of total market capitalization:

$$FLOW^*_{i,t} = \frac{TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1}}{MKT_{t-1}} \tag{4}$$

The index i references bond or equity funds, $TNA_{i,t}$ is the total net asset value of fund i at the end of month t, $r_{i,t}$ is the return on fund i over period t, and MKT_{t-1} is the lagged total market value of NYSE, AMEX, and NASDAQ.

Changes in each model specification relative to Model 1 are indicated in the model name, with any variable added to the model itself shown in bold.

Model 1*: $FLOW^*$ is dependent variable

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D^{FALL}_t + \mu_{r_{i,t-1}} r_{i,t-1} \\ &+ \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 2*: $FLOW^*$ is dependent variable and lagged market return used as a regressor

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D^{FALL}_t + \mu_{r^M_{t-1}} \mathbf{r^M_{t-1}} \\ &+ \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 3*: $FLOW^*$ is dependent variable and contemporaneous fund return used as a regressor (using instrumental variables)

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D^{FALL}_t + \mu_{r_{i,t}} \mathbf{\hat{r}_{i,t}} \\ &+ \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 4*: $FLOW^*$ is dependent variable and contemporaneous market return used as a regressor (using instrumental variables)

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D^{FALL}_t + \mu_{r^M_t} \mathbf{\hat{r}^M_t} \\ &+ \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 5*: $FLOW^*$ is dependent variable and no market return regressor included

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D^{FALL}_t \\ &+ \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 6*: $FLOW^*$ is dependent variable and January and December dummy variables used as regressors

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{i,FALL} D^{FALL}_t + \mu_{r_{i,t-1}} r_{i,t-1} + \mu_{i,DEC} \mathbf{D^{DEC}_t} \\ &+ \mu_{i,JAN} \mathbf{D^{JAN}_t} + \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

Model 7*: $FLOW^*$ is dependent variable; October, November, December and January dummies used as regressors; no fall dummy included

$$\begin{aligned} FLOW^*_{i,t} &= \mu_i + \mu_{i,SAD} SAD_t + \mu_{r_{i,t-1}} r_{i,t-1} + \mu_{i,OCT} \mathbf{D^{OCT}_t} + \mu_{i,NOV} \mathbf{D^{NOV}_t} + \mu_{i,DEC} \mathbf{D^{DEC}_t} \\ &+ \mu_{i,JAN} \mathbf{D^{JAN}_t} + \rho_{i,1} FLOW^*_{i,t-1} + \rho_{i,2} FLOW^*_{i,t-2} + \rho_{i,3} FLOW^*_{i,t-3} + \epsilon_{i,t} \end{aligned}$$

We report coefficient estimates from estimating each of these regression models (jointly for bond mutual funds and equity mutual funds for each model specification) in a GMM framework. $r_{i,t-1}$ and $r_{i,t}$ represent lagged and contemporaneous equity or bond fund returns, and r^M_{t-1} and r^M_t represent lagged and contemporaneous market returns. (To avoid problems introduced by using contemporaneous returns as a regressor in estimating our models, we use instrumental variables to generate predicted values, $\hat{r}^M_t$ or $\hat{r}_{i,t}$, and use the predicted values as a regressor in our model instead of the contemporaneous returns.) In all models, 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) and three lags of the dependent variable. In all but Model 7, a fall dummy variable is used as a regressor (D^{FALL}_t equals 1 during October, November, and December, and zero otherwise).

In Panel A we present coefficient estimates with HAC robust t-tests in parentheses. In Panel B we present the value of adjusted R^2 for each estimation, an F-test on the joint significance of the regression (labeled Test B1), a χ^2 statistic (with 2 degrees of freedom) for the null that the SAD and fall coefficient estimates are jointly zero (Test B2), and Lagrange Multiplier χ^2 test statistics for the presence of up to 12 lags of autocorrelation (AR) or ARCH (both with 12 degrees of freedom). In Panel C we present Wald χ^2 tests, with p-values below in parentheses, for the following: Test C1 tests the null that the SAD and fall variable coefficients are jointly zero across the bond and equity mutual funds for a given model, Test C2 tests the null the SAD coefficients are the same across the bond and equity funds for a given model, and Test C3 tests the null that the fall coefficients are the same across the bond and equity funds for a given model. Tests C1, C2, and C3 have 4, 1, and 1 degree of freedom respectively. 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
(HAC Robust T-Statistics)

	Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds
μ	0.285***	0.259**	0.418***	−1.957***	0.391***	0.147	0.281***	0.238**	0.250***	0.114	0.193**	0.126
	(3.136)	(2.153)	(6.403)	(-7.661)	(4.238)	(1.045)	(3.086)	(2.107)	(2.908)	(0.979)	(2.402)	(1.010)
μ_{SAD}	**0.229***	**-0.199***	**0.287***	**-0.135***	**0.297***	**-0.214***	**0.248***	**-0.200***	**0.356****	**-0.169**	**0.668***	**-0.175**
	(2.707)	(-1.890)	(11.362)	(-3.892)	(5.549)	(-3.571)	(3.032)	(-1.934)	(2.202)	(-1.007)	(3.976)	(-0.751)
μ_{FALL}	**-0.758***	**0.915***	**-0.806***	**0.916***	**-0.831***	**0.978***	**-0.784***	**0.928***	**-0.644***	**0.712****	.	.
	(-4.454)	(3.573)	(-14.85)	(10.439)	(-7.309)	(6.212)	(- 4.872)	(3.783)	(-2.596)	(2.406)	.	.
$\mu_{r_{t-1}}$	.	.	.	.	.	.	.	.	0.003	0.293*	−0.001	0.291*
	.	.	.	.	.	.	.	.	(0.219)	(1.884)	(-0.071)	(1.879)
$\mu_{r^M_{t-1}}$	0.021*	−0.006	.	.	.	.	.	.	.	.	.	.
	(1.716)	(-0.271)	.	.	.	.	.	.	.	.	.	.
$\mu_{\hat{r}_t}$	.	.	−0.082	5.063***	.	.	.	.	.	.	.	.
	.	.	(-1.017)	(7.963)	.	.	.	.	.	.	.	.
$\mu_{\hat{r}^M_t}$	.	.	.	.	−0.041	0.052	.	.	.	.	.	.
	.	.	.	.	(-0.532)	(0.363)	.	.	.	.	.	.
μ_{OCT}	.	.	.	.	.	.	.	.	.	.	−0.672***	0.684**
	.	.	.	.	.	.	.	.	.	.	(-3.052)	(2.374)
μ_{NOV}	.	.	.	.	.	.	.	.	.	.	−1.658***	0.878*
	.	.	.	.	.	.	.	.	.	.	(-4.460)	(1.697)
μ_{DEC}	.	.	.	.	.	.	.	.	−0.903***	0.559*	−2.423***	1.375**
	.	.	.	.	.	.	.	.	(-4.039)	(1.768)	(-5.294)	(2.165)
μ_{JAN}	.	.	.	.	.	.	.	.	−0.015	−0.350	−0.817	−0.465
	.	.	.	.	.	.	.	.	(-0.030)	(-0.619)	(-1.581)	(-0.643)
ρ_1	0.111	0.073	0.037**	−0.066**	0.051*	0.019	0.138*	0.079	0.083	0.007	0.033	−0.000
	(1.425)	(0.976)	(2.120)	(-2.150)	(1.847)	(0.378)	(1.927)	(1.054)	(1.003)	(0.092)	(0.398)	(-0.004)
ρ_2	0.262***	0.077	0.247***	−0.068**	0.258***	0.014	0.266***	0.076	0.277***	0.038	0.301***	0.045
	(6.124)	(1.168)	(28.176)	(-2.083)	(13.052)	(0.321)	(6.542)	(1.174)	(6.476)	(0.632)	(6.663)	(0.700)
ρ_3	0.218***	0.356***	0.262***	0.351***	0.261***	0.383***	0.207***	0.353***	0.240***	0.372***	0.271***	0.365***
	(4.701)	(7.763)	(16.727)	(19.389)	(10.028)	(13.806)	(4.631)	(7.945)	(5.014)	(8.760)	(5.792)	(8.447)

Panel B: Diagnostics

	Model 2 Equity	Model 2 Bonds	Model 3 Equity	Model 3 Bonds	Model 4 Equity	Model 4 Bonds	Model 5 Equity	Model 5 Bonds	Model 6 Equity	Model 6 Bonds	Model 7 Equity	Model 7 Bonds
Adj. R^2	0.169	0.196	0.163	0.318	0.162	0.196	0.168	0.204	0.207	0.218	0.237	0.209
Test B1	124.0***	123.3***	1306.0***	2832.6***	320.3***	378.6***	122.6***	125.0***	219.3***	153.7***	225.4***	166.4***
Test B2	20.0***	13.4***	225.3***	121.2***	54.0***	38.6***	23.8***	15.1***	6.7**	9.3***	.	.
AR	23.7**	11.2	19.9*	12.4	20.3*	12.6	22.0**	10.5	20.9*	15.8	16.2	15
ARCH	38.4***	13.6	41.3***	10.5	39.8***	13.6	32.3***	13.5	37.4***	12.9	35.7***	13.3

Panel C: Joint χ^2 Tests
(P-values)

	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Test C1	33.8	506.2	139.3	41.5	13.1	.
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0110)	.
Test C2	8.6	97.9	46.3	10.3	4.4	8.4
	(0.0035)	(0.0000)	(0.0000)	(0.0013)	(0.0356)	(0.0038)
Test C3	30.3	282.6	112.2	36.4	9.7	.
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0019)	.

Panel A: Parameter Estimates
(HAC Robust T-Statistics)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds	Equity	Bonds
μ	0.050***	0.006	0.047***	0.010*	0.076***	−0.059***	0.063***	0.002	0.046***	0.009*	0.048***	0.007	0.048***	0.006
	(3.770)	(0.950)	(3.452)	(1.753)	(9.862)	(-10.08)	(11.458)	(0.285)	(3.381)	(1.662)	(3.394)	(1.195)	(3.585)	(1.038)
μ_{SAD}	**0.010**	**-0.008***	**0.008**	**-0.008***	**0.015****	**-0.007****	**0.015****	**-0.009****	**0.010**	**-0.008***	**0.022***	**-0.011**	**0.046****	**-0.010**
	(1.484)	(-1.862)	(1.197)	(-1.742)	(7.998)	(-4.653)	(5.604)	(-3.208)	(1.536)	(-1.720)	(1.890)	(-1.398)	(3.035)	(-0.919)
μ_{FALL}	**-0.050****	**0.043****	**-0.049****	**0.041****	**-0.060****	**0.040****	**-0.059****	**0.042****	**-0.051****	**0.041****	**-0.048***	**0.038****	.	.
	(-4.577)	(4.261)	(-4.060)	(3.927)	(-16.14)	(9.118)	(- 9.331)	(6.864)	(-4.631)	(3.920)	(-2.314)	(2.710)	.	.
$\mu_{r_{t-1}}$	0.000	0.011	.	.	.	.	.	.	.	.	0.001	0.009	0.001	0.008
	(0.404)	(1.605)	.	.	.	.	.	.	.	.	(0.620)	(1.127)	(0.492)	(1.058)
$\mu_{r^M_{t-1}}$	.	.	0.003***	−0.000	.	.	.	.	.	.	.	.	.	.
	.	.	(3.426)	(-0.460)	.	.	.	.	.	.	.	.	.	.
$\mu_{\hat{r}_t}$	.	.	.	.	−0.016	0.160***	.	.	.	.	.	.	.	.
	.	.	.	.	(-1.564)	(10.938)	.	.	.	.	.	.	.	.
$\mu_{\hat{r}^M_t}$	.	.	.	.	.	.	−0.001	0.008	.	.	.	.	.	.
	.	.	.	.	.	.	(-0.172)	(1.191)	.	.	.	.	.	.
μ_{OCT}	.	.	.	.	.	.	.	.	.	.	.	.	−0.054***	0.037***
	.	.	.	.	.	.	.	.	.	.	.	.	(-2.870)	(2.666)
μ_{NOV}	.	.	.	.	.	.	.	.	.	.	.	.	−0.121***	0.040*
	.	.	.	.	.	.	.	.	.	.	.	.	(-3.423)	(1.726)
μ_{DEC}	.	.	.	.	.	.	.	.	.	.	−0.069***	0.032**	−0.185***	0.071**
	.	.	.	.	.	.	.	.	.	.	(-4.641)	(2.247)	(- 4.356)	(2.507)
μ_{JAN}	.	.	.	.	.	.	.	.	.	.	−0.016	0.002	−0.075*	−0.008
	.	.	.	.	.	.	.	.	.	.	(-0.455)	(0.071)	(- 1.767)	(-0.224)
ρ_1	−0.086	0.073	−0.098	0.115	−0.211***	0.023	−0.205***	0.028	−0.054	0.125	−0.124	0.055	−0.177	0.044
	(-0.788)	(0.853)	(-0.899)	(1.324)	(-8.306)	(0.806)	(- 8.725)	(0.561)	(-0.484)	(1.461)	(-1.061)	(0.630)	(- 1.515)	(0.517)
ρ_2	0.076	−0.010	0.097	−0.010	0.015	−0.110***	0.028	−0.050	0.115	−0.006	0.099	−0.075	0.094	−0.069
	(1.013)	(-0.169)	(1.144)	(-0.169)	(1.192)	(-4.339)	(1.556)	(-1.198)	(1.455)	(-0.096)	(1.199)	(-1.306)	(1.138)	(-1.120)
ρ_3	0.123***	0.422***	0.157***	0.441***	0.113***	0.419***	0.127***	0.447***	0.140***	0.432***	0.148***	0.449***	0.154***	0.447***
	(2.883)	(9.811)	(3.332)	(9.406)	(13.833)	(23.805)	(6.386)	(18.799)	(3.241)	(9.848)	(3.121)	(10.661)	(3.404)	(10.743)

Panel B: Diagnostics

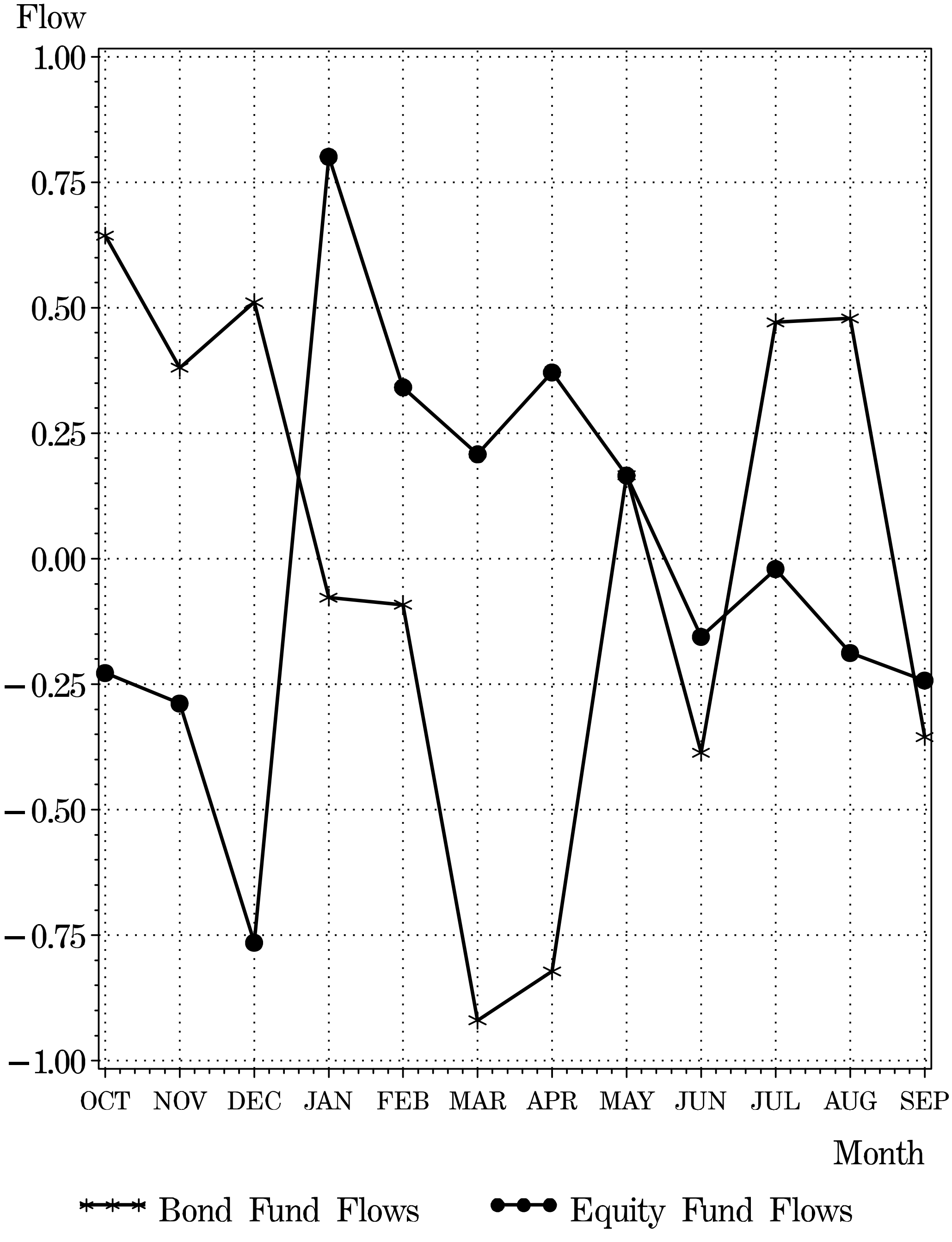
Adj. R^2	0.050	0.259	0.063	0.253	0.061	0.324	0.061	0.249	0.047	0.259	0.090	0.261	0.136	0.255
Test B1	57.3***	156.0***	44.3***	161.1***	826.7***	2154.2***	190.7***	527.5***	45.2***	157.3***	112.5***	188.9***	109.4***	242.8***
Test B2	32.5***	21.6***	25.8***	17.4***	262.1***	83.9***	89.9***	51.4***	30.1***	17.5***	5.6*	11.0***	.	.
AR	16.6	16.2	18.3	16.7	12.5	19.3*	12.8	18.3	16.8	15.6	16.9	21.7**	12.5	20.7*
ARCH	43.7***	13.9	39.9***	13.9	36.3***	18.4	36.5***	17.6	48.3***	13.7	42.2***	10.0	48.8***	9.8

Panel C: Joint χ^2 Tests
(P-values)

Test C1	45.2	35.9	398.0	125.6	41.2	16.0	.
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0030)	.
Test C2	3.9	2.9	82.2	30.4	3.8	5.9	10.3
	(0.0497)	(0.0908)	(0.0000)	(0.0000)	(0.0520)	(0.0155)	(0.0013)
Test C3	34.7	29.1	325.7	119.1	33.7	12.4	.
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)	.

Figure 1:

Average Monthly Equity and Bond Fund Flows
Percentage of Last Period Total Market Value, Deviation from Mean



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 equity funds and bond funds provided by CRSP over January 1992 through December 2002.