Seasonal Asset Allocation: Evidence from Mutual Fund Flows

by

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July 2010

JEL Classification: G11
Keywords: time-varying risk aversion; mutual fund flow seasonality; seasonal affective disorder; SAD

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Abstract

Investment managers and finance researchers alike are interested in the drivers of money flows into and out of mutual funds. Fund management companies have a financial incentive to retain existing capital under management and attract additional capital, while academic researchers find that flows represent an ideal setting in which to observe decision-making by individuals (in aggregate), since a broad cross-section of the population trades mutual funds and since flows convey the *quantity* of funds investors decide to allocate to one fund versus another. While previous studies have documented a relation between investor flows and past fund performance, we find a strong seasonality in fund flows that is consistent with a behavioral influence, that is, with some investors being influenced by seasonal changes in affect (mood). Extensive clinical research has shown that a substantial fraction of individuals around the world, amounting to tens of millions of people in North America alone, experience seasonal depression when the hours of daylight shrink in the fall, reversing as the days lengthen in the spring. The most severe form of this condition is seasonal affective disorder (SAD). Depression has been clinically linked to increased risk aversion, leading to the hypothesis that we should see seasonal movement in financial aggregates reflecting this seasonally-varying risk aversion. Consistent with this hypothesis, we document that substantial money moves from riskier to safer mutual funds in the fall, then from safer to riskier funds in the spring, controlling for the influence of past performance, advertising, and capital gains overhang on fund flows. While prior evidence regarding the influence of SAD on financial markets relies on seasonal patterns in the returns of asset classes, our paper provides the first direct dollar-flow evidence of SAD-related investing behavior by individual investors.

A large volume of research has uncovered strong predictability in mutual fund flows. For example, individuals invest heavily in funds with the highest prior-year returns, and disinvest weakly from funds with the lowest returns (Sirri and Tufano, 1998; Chevalier and Ellison, 1997; and Lynch and Musto, 2003). This return-chasing behavior indicates that individuals infer investment management quality from past performance, especially for past winning funds. More recently, Ben-Rephael, Kandel, and Wohl (2010a) show that flows to (from) US equity (bond) funds are strongly positively correlated with past equity market excess returns, with a strong return reversal in equities during the several months following strong flows. Their findings support the view that flows reflect investor sentiment. Indro (2004) also finds evidence consistent with equity fund flows being driven by investor sentiment. Further, Ben-Rephael, Kandel, and Wohl (2010b) examine daily equity fund flows in Israel and find strong autocorrelation in mutual fund flows as well as strong correlations of these flows with market returns, which appear to create a temporary price pressure.

Investors also react strongly to advertising of funds (Jain and Wu, 2000; and Gallaher, Kaniel, and Starks, 2006) and to other information that helps to reduce search costs (Huang, Wei, and Yan, 2007). In turn, the mutual fund industry spends more than half a billion dollars a year on advertising to attract investment inflows (see Pozen, 2002).

The benefits of attracting capital flows for mutual fund management companies are clear: in 2008, fund shareholders in the United States paid fees and expenses of 1.02 percent on equity funds and 0.79 percent on bond funds – with over 13 trillion dollars under management in all US-domiciled mutual funds (Investment Company Institute, 2008).

In this study, we document a heretofore unknown seasonality in mutual fund flows. Specifically, we show that flows to funds, controlling for the above-mentioned influences (and others), are strongly dependent on the season as well as the riskiness of the fund. Investors move money into safe funds during the fall, and into risky funds during the spring. These patterns of flows provide the first direct evidence that some investors exhibit seasonal patterns in risk aversion that are associated with the amount of daylight present during different seasons. This phenomenon coincides in timing with a medical condition known as seasonal affective disorder, or SAD. In addition, our results provide new evidence on SAD-related investing behavior that is based directly on what investors decide, specifically quantities of fund allocations, and that compliments and reinforces the returns-based evidence documented by prior research on seasonality.[1]

[1]Previous work by Kamstra, Kramer, and Levi (2003, 2010) and Garrett, Kamstra, and Kramer (2005) document seasonal

SAD is a seasonal form of depression. Medical evidence firmly demonstrates that as the number of hours of daylight drops in the fall, up to ten percent of the population suffers from clinical depression associated with SAD.[2] Up to an additional thirty percent experiences Subsyndromal SAD, or winter blues, a milder form of the same condition.[3] It has further been shown that depression is associated with increased risk aversion, both in general and in the context of making financial decisions in particular.[4]

We study mutual fund flows because they are largely the outcome of individual investors' decisions. According to the Investment Company Institute (2008), 44 percent of all US households owned mutual funds during 2007. Individuals held 86 percent of total mutual fund assets, with the remainder held by banks, trusts, and other institutional investors. The implication is that mutual fund flows predominantly reflect the investment decisions of individual investors, and that a broad cross-section of many types of individuals are involved in mutual fund markets. 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.

In this paper, we use a dataset comprised of actual monthly flows to 30 different mutual fund categories to build 5 different risk classes of funds: equities, hybrid, government fixed-income, corporate fixed-income, and money market. We study monthly flows to these fund asset classes with a model that controls for previously documented influences on flows; specifically, we control for past-year returns, recent advertising, and capital-gains overhang.[5]

To measure the impact of seasonal depression on investor behavior, we construct a novel variable based on medical clinical research data. This "SAD onset/recovery" variable reflects the change in the monthly proportion of SAD sufferers who are actively experiencing depressive symptoms (cumulated, starting in late summer, when only a small proportion of SAD patients experience their initial onset of symptoms). Thus, the variable that we use to capture SAD is a direct measure of individuals who are experiencing seasonal depression in a given month, rather than an indirect measure, such as the hours of daylight (which would impose an assumed parametric structure on the link between daylight and risk aversion due to SAD

patterns in returns to publicly traded stocks and bonds consistent with SAD, even when controlling for other known seasonal influences on returns, such as year-end tax effects. However, these papers do not show direct SAD-induced trading behavior by investors. Our paper provides the first quantity-based evidence of seasonally dependent investing behavior by mutual fund investors, which provides clear evidence of the impact of SAD on financial markets.

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

[3]See Kasper et al. (1989), Rosen et al. (1990), and Schlager et al. (1995), among others.

[4]For clinical and experimental evidence of the relationship between depression and increased risk aversion, see Pietromonaco and Rook (1987), Carton et al. (1992), Carton et al. (1995), and Smoski et al. (2008).

[5]Johnson and Poterba (2008) and Bergstresser and Poterba (2002) document that net flows to funds with large future capital-gains distributions are significantly lower than net flows to other funds.

effects).

Our empirical results are strongly consistent with an influential SAD effect on individual investor behavior. Specifically, after controlling for other (including seasonal) influences on flows, we find that SAD reduces net flows to equity funds by more than 4 billion dollars, and increases flows to money market funds by about 1.5 billion dollars, on average, during the fall month of October. Conversely, SAD increases net flows to equity funds by more than 4 billion dollars and reduces net flows to money market funds by over 1.5 billion dollars, on average, during the spring month of March.[6] We also find evidence of SAD-related flows to equity funds domiciled in Australia, where the relation of the calendar and seasons is offset by six months relative to the US. This evidence supports the view that individual flows are related to SAD, and not simply to calendar effects.

The remainder of the paper is organized as follows. In Section 1, we describe seasonal depression and explain how it can translate into an economically significant influence on a depression-affected investor's choice of assets. In Section 2, we briefly define the measures we use to capture the impact of seasonal depression on investment decisions. In Section 3 we discuss previously documented empirical regularities in flows, and we present evidence that the flow of capital into and out of mutual funds follows a seasonal pattern consistent with SAD. We introduce our US flows data in Section 4, and we present our main findings in Section 5. In Section 6 we present our findings based on Australian flows data. We describe additional robustness checks in Section 7. Section 8 concludes.

1 The Link between Seasons and Risk Aversion

The hypothesized link between seasons 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 investigations.

Regarding the first element of the link between seasons and risk aversion, namely the causal connection between hours of daylight and seasonal depression, evidence has been documented by many researchers, including Molin *et. al.* (1996) and Young *et. al.* (1997). Over the last couple of decades, a large

[6] To make up the balance, we believe that investors likely find other substitutes for safe money market funds, such as bank CDs or interest-bearing checking accounts.

industry has emerged informing people how to deal with the disorder, and offering products that create "natural" light to help sufferers cope with symptoms.[7] According to Rosenthal (2006), up to 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 seasons and risk aversion mentioned above, there is substantial clinical evidence on the negative influence depression has on individuals' risk-taking behavior. Pietromonaco and Rook (1987) find depressed individuals take fewer social risks and seem to perceive risks as greater than non-depressed individuals. Carton et al. (1992) and Carton et al. (1995) administer standardized psychological tests for risk aversion to depressed individuals, and find those individuals score significantly more risk averse than non-depressed controls. Additional studies focus specifically on financial contexts. For instance, Smoski et al. (2008) find depressed people exhibit greater risk aversion in an experiment that includes monetary payoffs. Harlow and Brown (1990) document the connection between sensation seeking (a measure of inclination toward taking risk on which depressed individuals tend to score much lower than non-depressed individuals) 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 scores and to blood levels of neurochemicals associated with sensation seeking.[8] 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, roughly 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 approximately 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

[7]Examples of popular books by leading SAD researchers that are devoted to approaches for dealing with SAD are Lam (1998a) and Rosenthal (2006).

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

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

Evidence in the medical and psychology literatures suggests that for most people who suffer from SAD, depression and other symptoms typically begin in the fall and alleviate by the end of winter. A subset of people, however, start suffering earlier and/or continue suffering until later. Medical researchers have established that the driving force behind SAD is lack of sunlight, literally the amount of time between sunset and sunrise (which is at its minimum at summer solstice, increases most quickly at autumn equinox, peaks at winter solstice, and drops most quickly at spring equinox), not lack of *sunshine*, which depends on the presence of cloud cover. Thus we follow Kamstra et al. (2010) and proxy for the influence of SAD on market participants using a variable based on the timing of the onset of and recovery from depression among individuals who are known to suffer from SAD. The variable is constructed as follows, based on data compiled in two studies of hundreds of SAD patients in Chicago and Vancouver respectively by Young *et. al.* (1997) and Lam (1998b).

First we construct a SAD "incidence" variable, which reflects the monthly proportion of SAD-sufferers who are actively experiencing SAD symptoms in a given month. The incidence variable is constructed by cumulating, monthly, the proportion of SAD-sufferers who have begun experiencing symptoms (cumulated starting in late summer when only a small proportion of SAD patients have been diagnosed with onset) and then deducting the cumulative proportion of SAD-sufferers who have fully recovered from SAD. This incidence variable varies between zero percent, in summer, and close to 100 percent in December/January. Because the variable is an *estimate* of the true timing of onset and recovery among SAD-sufferers in the more general North American population, we use instrumental variables to correct for a possible error-in-variables bias (see Levi (1973)).[9] Finally, we calculate the monthly change in the instrumented series to produce the monthly SAD onset/recovery variable that we use in this study. We denote SAD onset/recovery as $\hat{OR}_t$ (short for onset/recovery, with the hat indicating that the variable is the fitted

[9]To produce the instrumented version of incidence, first we smoothly interpolate the monthly incidence of SAD to daily frequency using a spline function. Next we run a logistic regression of the daily incidence on our chosen instrument, the length of day. (The nonlinear model is $1/(1 + e^{\alpha+\beta day_t})$, where day_t is the length of day t in hours in New York and t ranges from 1 to 365. This particular functional form is used to ensure that the fitted values lie on the range zero to 100 percent. The $\hat{\beta}$ coefficient estimate is 1.18 with a standard error of 0.021, the intercept estimate is -13.98 with a standard error of 0.246, and the regression R^2 is 94.9 percent.) The fitted value from this regression is the instrumented measure of incidence. Employing additional instruments, such as change in the length of the day, makes no substantial difference to the fit of the regression or the subsequent results using this fitted value.

value from a regression, as noted above). More specifically, the monthly variable $\hat{OR}_t$ is calculated as the value of the daily instrumented incidence value on the 15th day of a given month minus the value of the daily instrumented incidence value on the 15th day of the previous month.[10]

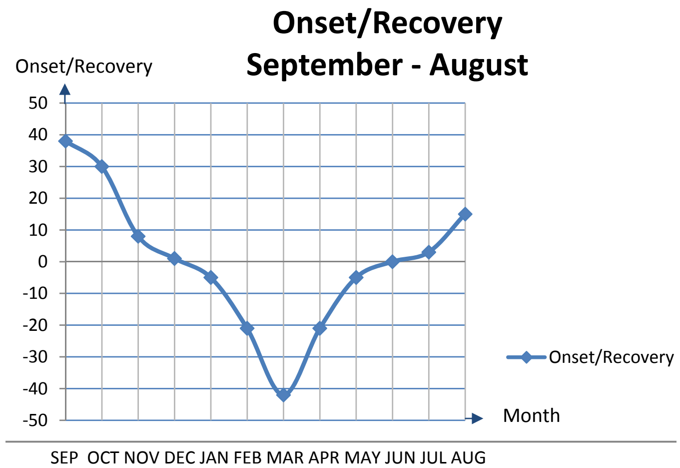

Figure 1: The onset/recovery variable reflects the change in the proportion of SAD-affected individuals actively suffering from SAD. The monthly series, calibrated to the 15th day of each month, is based on the clinical incidence of SAD symptoms among patients who suffer from the condition.

$\hat{OR}_t$ reflects the *change in the proportion of SAD-affected individuals actively suffering from SAD.* The monthly values of $\hat{OR}_t$ are plotted in Figure 1, starting with September and ending with August. Notice that the measure is positive in the summer and fall and negative in the winter and spring. Its value peaks near the fall equinox and reaches a trough near the spring equinox. The movement in $\hat{OR}_t$ over the year should capture the hypothesized opposing patterns in flows across the seasons, should they exist, without employing the two (perhaps problematic) variables used by Kamstra et al. (2003): neither the simple fall dummy variable nor the length-of-day variable is necessarily directly related to the onset and recovery from SAD.[11]

Some additional features of our onset/recovery variable are important to note. First, our onset/recovery variable is based directly on the clinical incidence of SAD in individuals, unlike Kamstra et al. (2003)'s variables. Second, our onset/recovery variable spans the entire year, whereas Kamstra et al. (2003)'s length of night and fall dummy variables take on non-zero values during the fall and winter months only (and therefore do not account for the portion of SAD-sufferers who experience symptoms earlier than fall

[10]The values of $\hat{OR}_t$ by month, rounded to the nearest integer and starting with July, are: 3, 15, 38, 30, 8, 1, -5, -21, -42, -21, -5, 0. These values represent the instrumented *change* in incidence of symptoms.

[11]In an untabulated regression, we compare the performance of $\hat{OR}_t$ to the two variables Kamstra et al. (2003) originally employed in their model and find qualitatively similar results. Importantly, conclusions relating to the existence of a SAD-related seasonal cycle in mutual fund flows remain intact.

or later than winter). In light of these points, we conduct our analysis using the onset/recovery variable.

3 Seasonality in Mutual Fund Flows

While previous research has studied the influence of SAD on asset returns, the SAD hypothesis also has implications for the quantities of capital flowing between different classes of assets. Quantity is a *decision* variable for investors, unlike a market price which is a consequence of supply and demand. Thus, we investigate whether investors adjust the riskiness of their portfolios by moving money between different risk classes of assets. According to the Investment Company Institute and the Security Industry Association (2005), nearly 57 million US households owned equity directly or through mutual funds in 2005. Of those, 90 percent own stock mutual funds, and nearly half own individual stock. Further, according to the Investment Company Institute (2008), 44 percent of all US households owned mutual funds in 2007. Individuals held 86 percent of total mutual fund assets, 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 quantity decisions of individual investors, and that a large cross-section of individuals are involved in mutual fund markets. 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.

In our analysis of mutual fund flows, our questions are twofold. First, does the increased risk aversion that some investors experience with diminished length of day in autumn lead to a shift from risky funds into low-risk funds? Second, do investors move capital from safe funds back into risky funds after winter solstice, coincident with increasing daylight and diminishing risk aversion? Prior to investigating these questions, we discuss several important considerations that we must take into account.

3.1 Controlling for Capital-Gains Distributions

Capital gains and (to a much lesser extent) dividend distributions by mutual funds to shareholders follow a seasonal pattern, even before the 1986 Tax Reform Act (TRA) synchronized the tax year-end for all funds to October 31 (see, for example, Gibson, Safieddine, and Titman, 2000). This requirement of TRA went into full effect by 1990.

Table 1 illustrates the seasonality in capital gains and dividend distributions to shareholders by presenting the frequency of such distributions that are paid during each calendar month, computed over the 1984 to 2007 period using the CRSP Mutual Fund Database. Panel A presents results for capital gains distributions, while Panel B presents results for dividend distributions. The results show that capital gains are predominantly paid at the end of the calendar year, with 9.8% being during paid during November, and 72% during December. To a much lesser extent, dividend distributions are also paid more frequently at the end of the year, with 14.1% being paid during December. In untabulated results, we find a similar seasonality in distributions when we focus on the post-TRA period (*i.e.*, 1990-2007).

Since distributions of capital gains are highly seasonal, we must consider their effect on seasonal variations in mutual fund flows. There are a couple potential influences that distributions may have on seasonal flow patterns. First, we would expect that flows to funds increase when distributions are large, simply by reinvestment of such distributions by investors. To address this, we assume that the choice of the reinvestment of capital gains and dividend distributions is usually made once by a new shareholder, who instructs the fund company to automatically reinvest (or to not reinvest) distributions, and that this decision is not subsequently changed. Thus, we consider flows from reinvestment of distributions as "passive flows." Fortunately, our dataset reports such flows separately from other shareholder flows, and we, therefore, exclude reinvestments from our measure of flows.

However, another influence of distributions is that potential shareholders may delay their purchase or advance their sale of shares of a fund with substantial realized capital gains to be distributed in the near future. For instance, suppose that a fund realized a capital gain of 100 dollars by October 31, based on trades during the year ending at this date. If the fund does not distribute these gains until December, shareholders may avoid purchasing such shares until the ex-distribution date to avoid the associated taxation. Also, investors who planned to sell the shares in January may sell before the distribution in December in order to avoid the capital gain realization, depending on the magnitude of the capital gain that will be realized by their sale of fund shares. For example, consider a shareholder who purchased the stock part way through the year, and only 10 dollars of the year's 100 dollars in total capital gains accrued since the time of his recent purchase. That shareholder may sell his shares prior to the dividend distribution instead of holding the stock and incurring the taxation associated with the 100 dollar capital gain distribution. (He would be unable to offset the 100 dollar capital gain with its accompanying 90 dollar capital loss in the same tax year.)

Expected capital gains distributions likely impact the tendency of shareholders to buy or sell a fund, especially in November and December. Investors, of course, cannot perfectly determine the realized capital gains of a fund during the year ending October 31, but likely estimate this from the return of the fund during that period. Accordingly, we include this return as a control for the effect of capital-gains overhang on flows – only during November and December of each year. We consider a variety of alternative measures of this overhang in our robustness checks section.

3.2 Other Empirical Regularities in Mutual Fund Flows

Various other 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). For instance, 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. Some researchers have looked for fund-specific characteristics that might explain fund flows. See for instance Sirri and Tufano (1998) and Del Guercio and Tkac (2008), who variously study the impact on fund flows of fund-specific characteristics including fund age, investment style, and Morningstar rating.

4 Data

We obtained several datasets from the Investment Company Institute (ICI) that consist of monthly flows to 33 mutual fund investment categories, covering altogether the date range of January 1, 1984 to January 31, 2010. The need for lagged values restricts our range of data to start in January 1985, and concerns about the chaotic flows during the financial crisis, in particular flows in and out of money market funds, convinced us to end our sample in December 2006. For each objective category during each month, the ICI provided the total sales, redemptions, exchanges, reinvested distributions, and (end-of-month) total net assets (TNA), aggregated across all funds within that category. Exchanges consist of exchanges from other same-family funds into a given fund (exchanges in) and exchanges from a given fund to other same-family funds (exchanges out). Table 2 shows the categories of funds we employ. We group the fund categories into five asset classes, as shown in the table. These asset classes include: “equity,” “hybrid,” “corporate fixed income,” “government fixed income,” and “money market.” Flows and assets are aggregated across all investment categories to arrive at total asset class-level flows and assets.[12] We compute "active" net monthly flows to asset class i during month t, as a proportion of month $t-1$ total net assets, as follows:

$$NetFlow_{i,t} = \frac{Sales_{i,t} - Redemptions_{i,t} + ExchangesIn_{i,t} - ExchangesOut_{i,t}}{TNA_{t-1}}.$$

Note that we do not include reinvested distributions in flows, as we assume that those are "passive flows."

Another measure of flows we consider is monthly net exchanges to asset class i during month t, as a proportion of month $t-1$ total net assets:

$$NetExchange_{i,t} = \frac{ExchangesIn_{i,t} - ExchangesOut_{i,t}}{TNA_{t-1}}.$$

We explain our interest in this alternate measure later.

In Table 3, we report summary statistics on our data, including monthly asset class fund net flows in Panel A, monthly asset class net exchanges in Panel B, explanatory variables used in our regression models in Panel C, and value-weighted returns to holding the various fund classes in Panel D. The range of the data extends from January 1985 through December 2006. As previously mentioned, fund flows are reported as a proportion of the fund's last period total net assets.

From Panel A, we can see that the mean monthly net equity class fund flow is 0.59 percent of equity class TNA. The hybrid class has a mean monthly flow around 0.8 percent of hybrid TNA, and the corporate fixed income class has very similar mean flows of 0.79 percent of TNA. The government fixed income class has mean monthly flows of about 0.65 percent of TNA, and the money market asset class has mean monthly flows of about 0.38 percent of TNA. Asset class fund flow standard deviations range from a low of 0.82 percent for the equity class to a high of over 2 percent for the money market and government fixed income classes. All of the series are somewhat skewed and leptokurtotic.

Panel B displays net exchange flows, which should and do net to within about a basis point of zero. The volatility of net exchanges is smaller than net flows, the skewness is negative compared to the positive skewness of net flows, and the net exchanges are strongly fat-tailed, evidenced by kurtosis 8 to 12 times that of net flows.

In Panel C we present statistics for advertising and savings. Our advertising variable is monthly print

[12] We omit three fund categories from our analysis: Taxable Money Market - Non-Government, National Tax-Exempt Money Market, and State Tax-Exempt Money Market. While these are ostensibly most similar to our money market category (which includes only funds classified as Taxable Money Market - Government), we sought a money market category that represents the safest category of funds. Wermers (2010) shows evidence that investors considered the Taxable Money Market - Government category as the safe haven during the money fund crisis of September 2008. However, our results are qualitatively unchanged if we instead include the three omitted funds in our money market category.

advertisement expenditures by mutual fund families (detrended by dividing by the previous year's total advertisement expenditure).[13] Our savings variable is calculated by subtracting Real Personal Consumption Expenditures (BEA series ID PCEC96) from Real Disposable Personal Income (BEA series ID DSPIC96), divided by PCEC96, multiplying by 100 and dividing by 12, lagged one period. Advertisements trend upward during our sample period even after detrending by the 12 month moving average, though only slightly, and savings average to over 1.5% per month. Even the more conservative BEA savings rate (which is reported on in the press) shows an average monthly savings rate of 0.4% over this period.[14]

Summary statistics for the one-year moving average return (R^{Year}, our return-chasing proxy) and the cumulated return ($R^{CapGains}$, our capital gains proxy) are displayed in Panel C. Summary statistics for the monthly excess fund returns are displayed in Panel D. The return for month t and fund i is calculated as $R_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} - Flow_t}{TNA_{t-1}}$. All these return data reveal familiar patterns, with equity returns being the largest and the most volatile, declining virtually monotonically across categories ordered with hybrid funds second, corporate bond funds third, government fixed income fourth, and money market funds last. The order in which we present our data is thus consistent with declining idiosyncratic risk, and the excess returns show a monotonically declining CAPM β suggesting a declining exposure to systematic risk across this ordering of fund families. We also present the coefficient on our SAD variable from a regression of excess returns on onset/recovery from SAD, which we describe shortly.

In Figures 2 through 4 we consider unconditional patterns in asset class fund flows. More formal analysis follows. Consider first Panel A of Figure 2, in which the solid line corresponds to the the monthly average flows for the equity asset class. The unconditional seasonal patterns in equity class flows are consistent with SAD having an impact on flows. During the fall months, as daylight diminishes, individuals prone to SAD become depressed and more risk averse. If their risk aversion causes them to shift assets away from risky asset classes and toward safe asset classes, we should see lower-than-average net equity flows in the fall months, and we do. Similarly, as daylight become more plentiful in the winter months through to the spring, SAD-affected investors become less averse to risk, and should be more willing to hold risky funds. Accordingly, we see equity net flows are higher than average during that period. Overall, the

[13] We obtain the monthly advertising expenditure data from Gallaher, Kaniel, and Starks (2006), Figure 3. Their series covers advertisements in over 288 print publications over 1992-2001; for sample dates outside that period we use the average monthly values calculated using the 1992-2001 period. Reuter and Zitzewitz (2006) report that most mutual fund advertisements are print ads.

[14] We have conducted robustness checks using the BEA personal saving rate (series ID PSAVERT) in place of the savings variable based on PCEC96 and DSPIC96 and found both this series and our savings variable behave very similarly, with use of the BEA personal savings rate making only minor qualitative changes to our results.

Average Monthly Net Flows: Equity and Hybrid

Panel A Equity | Panel B Hybrid

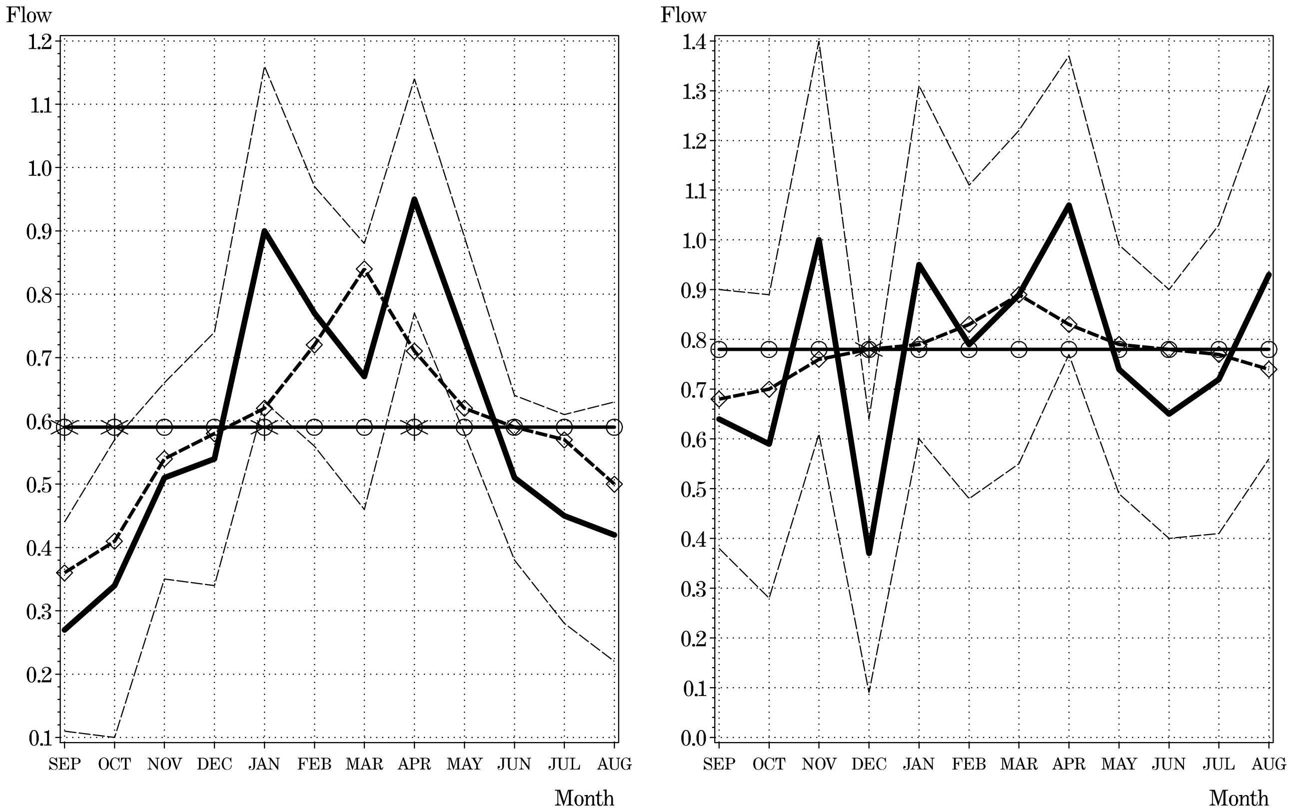

Figure 2: Panel A contains monthly average **equity** asset class fund net flows as a proportion of equity class TNA, indicated with a solid line, and average fitted values implied by the onset/recovery coefficient from estimating Equation (1), indicated with a dashed line with diamonds. Panel B contains monthly average **hybrid** asset class fund net flows as a proportion of hybrid class TNA, indicated with a solid line, average fitted values implied by the onset/recovery coefficient from estimating Equation (1), indicated with a dashed line with diamonds. The plots also include a 90% confidence interval around the monthly means (shown with light dashed lines) and the average flow throughout the year (represented by solid lines with circles – and an x mark in cases where the average return falls outside of the confidence interval). The data, provided by the Investment Company Institute, span January 1985 through December 2006.

lower-than-average flows in the fall and higher-than-average flows in the winter/spring are consistent with SAD-affected investors shifting their portfolios between risky and safe funds depending on their seasonally varying risk aversion. The light dotted lines surrounding the solid line are the 90% confidence interval around the average monthly flows.[15] Consistent with the intuition from the seasonal pattern of flows,

[15]There are several approaches one could adopt to calculate the confidence interval around the mean monthly flows. The simplest is to use the standard deviation of the monthly mean flows directly. However, this would ignore information about the cross-sectional variability of flows across the fund asset classes. Instead, we form a system of equations with the flows data and estimate a fixed-effects model with twelve dummy variables (one for each month). In order to leverage the information in the cross-section more effectively, we work with slightly more disaggregated data than the five fund classes, using instead the nine classes we describe later in the paper. Consistent with the typical implementation of a fixed effects model, we allow each sub-class series within an asset class to have a different mean, while estimating a single set of parameter values for the variables each sub-class series in an asset class has in common, in this case the monthly dummy variables. The equity fund asset class is split into two sub-classes, "risky equity" and "safe equity." "Hybrid" remains as previously defined. "Corporate fixed income" is split into "global bond" and "US corporate bond". "Government fixed income" is split into "munis," "medium and short-term government," and "general-term government." The "money market" asset class remains as previously defined. From this regression we obtain the standard errors on the fund flow monthly dummies to form the confidence intervals around

we see several instances of statistically significant (unconditional) deviations of the equity fund flows from annual mean flows, lower in the the fall, higher in the winter/spring. The dashed line marked with diamonds represents the average monthly fitted values from a regression model that includes SAD onset/recovery as an explanatory variable. We develop this model fully below, but for now it suffices to note that the fitted value seems to track the unconditional seasonal pattern in flows fairly well.

Average Monthly Net Flows:
Corporate Fixed Income and Government Fixed Income

Panel A
Corporate Fixed Income

Panel B
Government Fixed Income

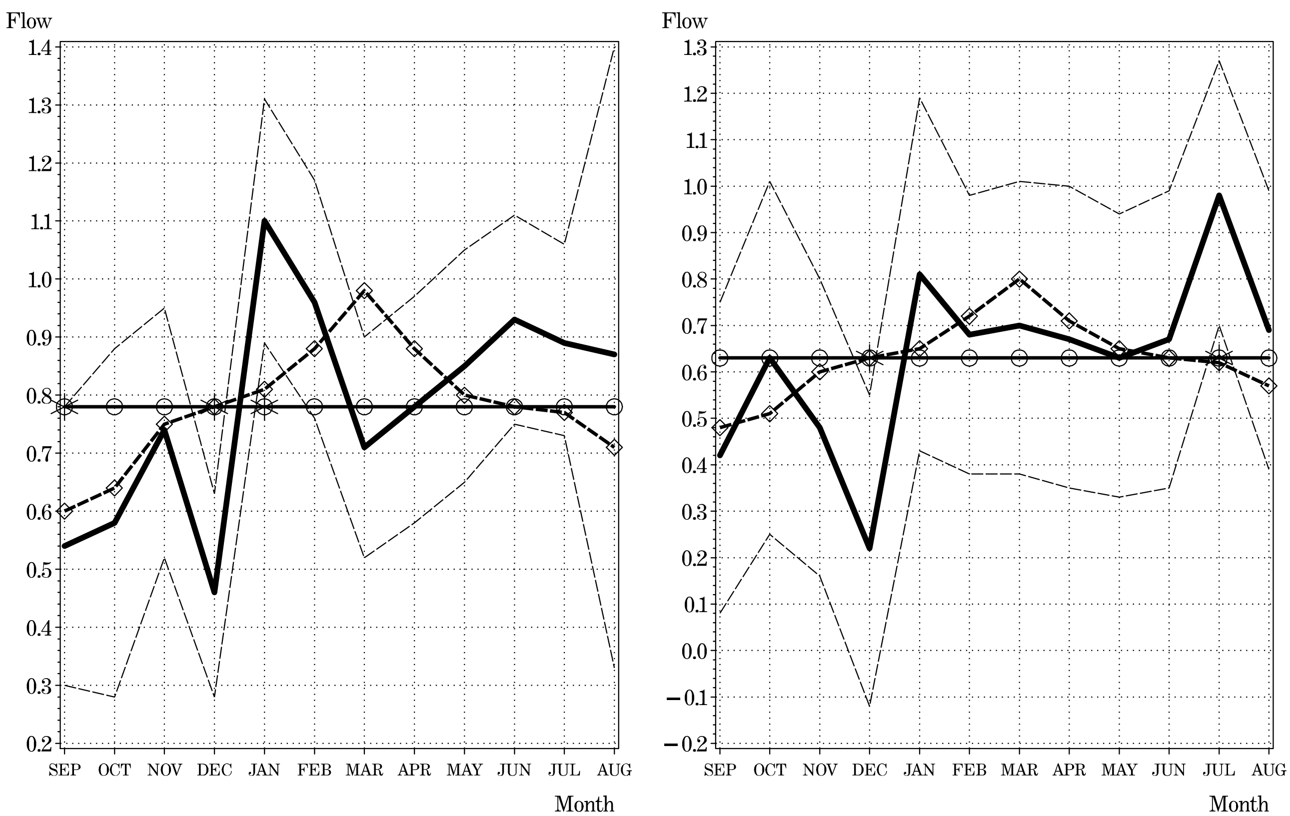

Figure 3: Panel A contains monthly average **corporate fixed income** asset class fund net flows as a proportion of corporate fixed income TNA, indicated with a solid line, and average fitted values implied by the onset/recovery coefficient from estimating Equation (1), indicated with a dashed line with diamonds. Panel B contains monthly average **government fixed income** asset class fund net flows as a proportion of government fixed income TNA, indicated with a solid line, average fitted values implied by the onset/recovery coefficient from estimating Equation (1), indicated with a dashed line with diamonds. The plots also include a 90% confidence interval around the monthly means (shown with light dashed lines) and the average flow throughout the year (represented by solid lines with circles – and an x mark in cases where the average return falls outside of the confidence interval). The data, provided by the Investment Company Institute, span January 1985 through December 2006.

In Panel B of Figure 2 we plot the monthly average flows for the hybrid class. We see similar patterns to that presented for equity fund flows: below-average flows in the fall and above-average flows in

the monthly mean flows. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. The instruments used for the regression are the 12 month dummy variables.

the winter/spring, though the unconditional pattern is markedly less pronounced than for equity funds. Figure 3 contains plots of the monthly average flows for the corporate fixed income asset class (Panel A) and the government fixed income asset class (Panel B). The corporate and government fixed income flows also exhibit the pattern of lower flows in the fall and higher flows in the winter/spring, though again the patterns are less pronounced than for equity funds.

The finding of the strongest seasonal pattern in equity flows is consistent with the relative ranking of the riskiness of the fund categories (measured by fund excess return beta and SAD coefficient estimates shown in Table 3) and is consistent with practitioner classifications of the risk involved in holding these various fund classes.

Average Monthly Net Flows: Money Market

Panel A — Money Market | Panel B — Money Market

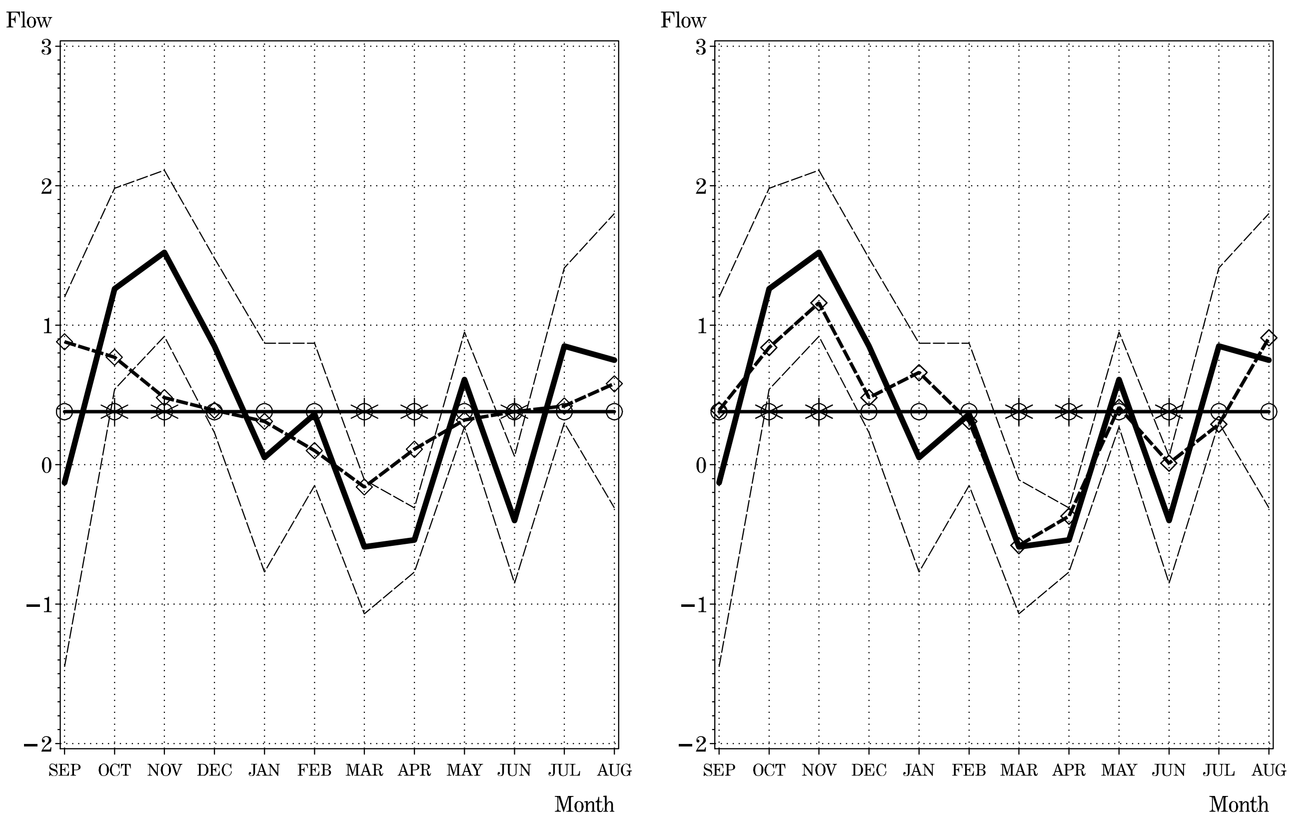

Figure 4: Panel A contains monthly average **money market** asset class fund net flows as a proportion of money market TNA, indicated with a solid line, and average fitted values implied by the onset/recovery coefficient from estimating Equation (1), indicated with a dashed line with diamonds. Panel B contains monthly average **money market** fund net flows as a proportion of money market TNA, indicated with a solid line, and average fitted values implied from estimating Equation (3), indicated with a dashed line with diamonds. The plots also include a 90% confidence interval around the monthly means (shown with light dashed lines) and the average flow throughout the year (represented by solid lines with circles – and an x mark in cases where the average return falls outside of the confidence interval). The data, provided by the Investment Company Institute, span January 1985 through December 2006.

In Panel A of Figure 4, we plot the money market asset class flows. In contrast to the asset classes considered to this point, the money market flows exhibit a much stronger long-lagged autocorrelation (particularly at the 6-month and 12-month lags).[16] The differential nature of autocorrelation in money market funds relative to other funds may arise due to flows associated with buying, holding, and rolling over common money market instruments which have 1-month, 3-month, 6-month, and 12-month maturities. In light of this difference, we present in Panel B of Figure 4 money market monthly flows together with the average fitted values implied from estimating a model that accounts for autocorrelation (the model is developed fully below), indicated by a dashed line with diamonds. Accounting for autocorrelation in the money market fund flows dramatically improves the ability of the model to account for the unconditional seasonality in fund flows. Indeed, analysis of the residuals from this model would show no remaining seasonality.

5 Results

In the previous section we presented unconditional plots which suggest that flows into and out of risky mutual funds exhibit seasonal patterns consistent with SAD. We turn now to more formal conditional analysis.

5.1 Regression Model

The regression model we consider is:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}} \hat{OR}_t + \mu_{Ads} Ads_t + \mu_{i,R^{Year}} R^{Year}_{i,t} + \mu_{i,CapGains} R^{CapGains}_{i,t} \\ &+ \mu_{i,Savings} Savings_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where i references the mutual fund asset class. The dependent variable, $NetFlow_{i,t}$, is the month t fund net flow expressed as a proportion of month $t-1$ total net assets. $\hat{OR}_t$ is the SAD onset/recovery variable, Ads_t is monthly print advertisement expenditures by mutual fund families (normalized by the prior year's ad expenditures), and the remaining explanatory variables are as follows. $R^{Year}_{i,t}$ is the return to fund asset class i over the prior 12 months (*i.e.* from month $t-13$ through to month $t-1$), included to control for return-chasing flows. $R^{CapGains}_{i,t}$ is included to control for the influence of capital gains overhang on flows. For the months November and December, $R^{CapGains}_{i,t}$ equals the cumulated return to holding the fund from the previous year's November (the start of the tax year for mutual funds) to the current year's October.

[16] We report specific autocorrelation coefficient estimates and their statistical significance later, in Table 6.

$R_{i,t}^{CapGains}$ is set to zero in all months other than November and December. $Savings_{i,t}$ is personal savings, lagged one period.

We estimate Equation (1) as a system of equations using Hansen's (1982) GMM and Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors.[17] Results from estimating this set of equations are shown in Table 4. 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. Our use of HAC standard errors is consistent with the strong statistical evidence of autocorrelation. The bottom of Panel A contains adjusted R^2 for each asset class model and χ^2 statistics for testing for the presence of up to 12 lags of autocorrelation (AR) or ARCH. The test for ARCH is a standard LM test of order 12. See Engle (1982). To perform the test for autocorrelation, we augment our regression with 12 lags of the residuals, estimate MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors with OLS and test for the joint significance of these terms.

Consider first the coefficient estimates on the onset/recovery variable. The equity, hybrid, corporate and government fixed income asset classes all have negative coefficients on $\hat{OR}_t$, but only equity fund flows display statistically significant negative effects, and equity funds also display the largest economic magnitude effect of these four. Recall that the onset/recovery variable itself is positive in the fall and negative in the winter/spring (see Figure 1). Thus the implication is that equity fund flows are expected to be below-average in the fall and above-average in the winter/spring, as displayed in the unconditional plot in Figure 2. The onset/recovery variable is positive and statistically significant for the money market asset class, implying money market fund flows are expected to be above average in the fall and below average in the winter/spring, again as we see unconditionally.

In Panel B we present statistics testing the joint significance of the onset/recovery coefficient estimates across the asset classes, using Wald χ^2 statistics based on the HAC covariance estimates. The first tests whether the onset/recovery estimates are jointly equal to zero across the series. We strongly reject the null of no SAD-related seasonal effect. The second joint statistic tests whether the onset/recovery coefficient estimates are jointly equal to each other, not necessarily zero. This null is strongly rejected as well,

[17] Our use of HAC standard errors is due to the fact that autocorrelation is a prominent feature of all classes of fund flows. See Warther (1995), Remolona, Kleiman, and Gruenstein (1997), and Karceski (2002), among others. Our results are virtually identical if we instead include sufficient lags of the dependent variable to remove significant evidence of autocorrelation, and are presented later. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$ The instruments used for the regression are the explanatory variables.

supporting the position that the safe and risky funds do indeed exhibit different seasonal cycles in flows related to the onset/recovery variable. We also provide a χ^2 goodness-of-fit test of our model.[18] The goodness-of-fit test indicates that the over-identifying moment restrictions we use to estimate the model are not rejected.

Consider now other variables in the model. The advertising expenditure coefficient estimate is positive only for the equity class, and is strongly significantly negative for only corporate fixed income. This finding suggests that while fund family advertising may attract flows to equity funds, it likely does so at the expense of relatively safer funds. The return over the previous year, R^{Year}, has a positive and significant coefficient estimate for all asset classes, consistent with flows chasing performance. The capital gains overhang variable is negative for all classes except money market funds, which is consistent with investors having a tendency to avoid purchasing funds that have substantial realized gains to distribute.[19]

5.2 Fit of the Model

Recall that previously we briefly mentioned the dotted lines with diamonds that appear in Figures 2, 3, and 4. Those diamond-marked lines represent fitted values from estimating the regression model reported in Table 4: Equation (1). (The only exception is the diamond-marked line in Panel B of Figure 4, which is the fitted value from a model we present later.) The fitted values demonstrate graphically the ability of the regression model to fit the average monthly seasonal variation in fund flows. The *time-series* fit of the models is shown in Figures 5, 6, and 7. Panel A of Figure 5 corresponds to the equity fund flows, Panel B of Figure 5 corresponds to hybrid fund flows, Panels A and B of Figure 6 correspond to corporate and government fixed income fund flows respectively, and Panel A of Figure 7 depicts the fit of the money market fund flows. (We discuss Panel B of Figure 7 later.) For all the series, the fit of the model is less precise over the first few years of the sample, consistent with the very volatile equity markets during the late 1980s. The spikes in flows during this period mostly coincide with extreme market events, such as the October 1987 equity market crisis. In addition, our ICI data is likely less precise prior to 1996.

As a robustness check we estimated Equation (1) after having truncated pre-1996 data from our sample. We find (in untabulated results) that our findings on the impact of the onset/recovery variable are

[18] Hansen (1982) details conditions sufficient for consistency and asymptotically normality of GMM estimation and shows that the optimized value of the objective function produced by GMM is asymptotically distributed as a chi-square, providing a goodness-of-fit test of the model.

[19] In untabulated tests, we find that the proxy for expected money market fund capital gains during November and December, the return on the category from November 1 to October 31, appears to capture bigger year-end return-chasing in money fund categories due to, perhaps, selling of equity funds for tax-loss realization–since money market funds do not normally distribute significant capital gains for investors to worry about.

qualitatively unchanged.

Time Series of Net Flows: Equity and Hybrid

Panel A Equity | Panel B Hybrid

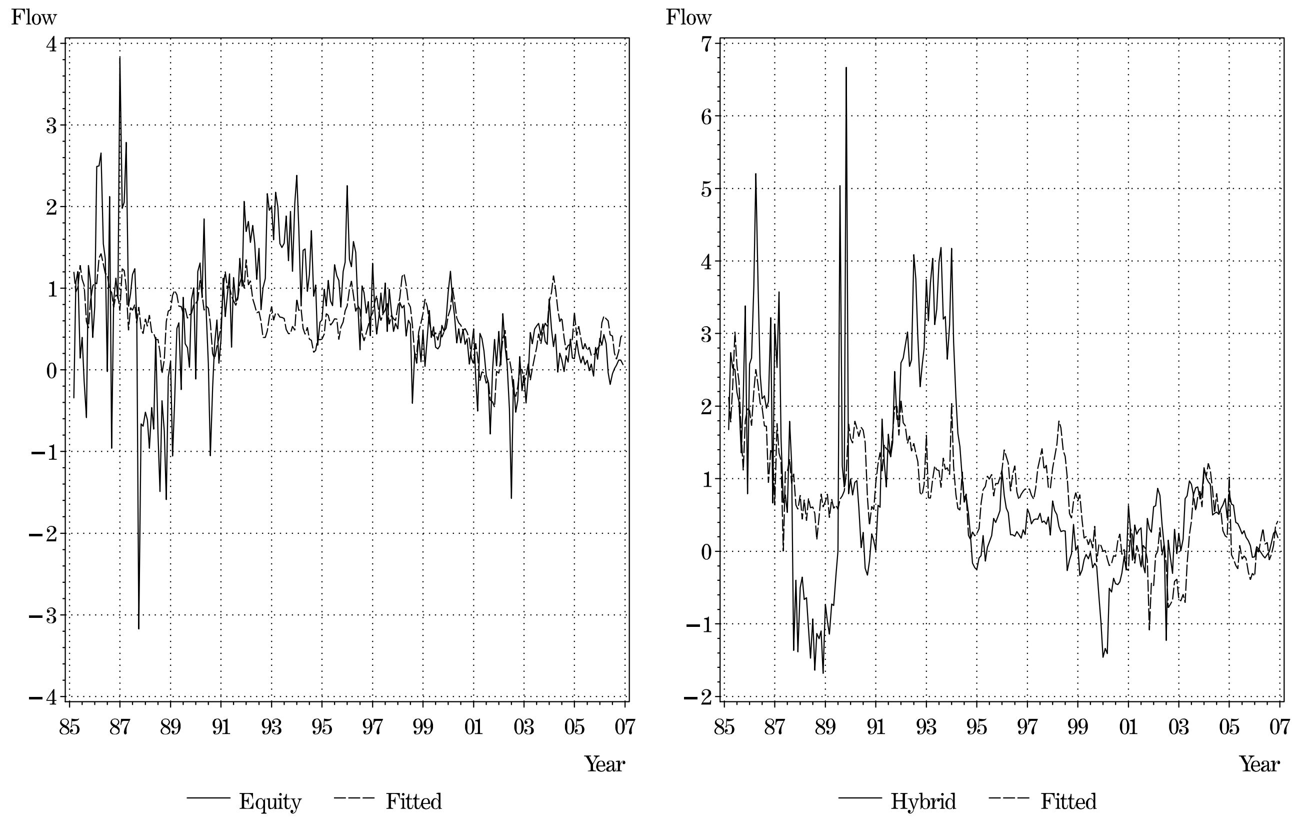

Figure 5: Panel A contains the time series of monthly **equity** fund net flows as a proportion of equity class TNA, indicated with a solid line, and the monthly fitted values from estimating Equation (1),indicated with a dashed line. Panel B contains the time series of monthly **hybrid** fund net flows as a proportion of hybrid class TNA, indicated with a solid line, the monthly fitted values from estimating Equation (1), indicated with a dashed line. The data, provided by the Investment Company Institute, span January 1985 through December 2006.

5.3 Investor Sentiment and Mutual Fund Flows

Ben-Rephael, Kandel, and Wohl (2010a) also explore flows between fund categories, finding that monthly shifts between bond funds and equity funds in the US are related to aggregate equity market excess return movements. The flows they consider are net exchanges (exchanges in minus exchanges out), in contrast to the net flows (net exchanges plus sales net of redemptions) typically considered (and used to this point in our own exploration of seasonality in flows). Ben-Rephael, Kandel, and Wohl (2010a) suggest that net exchanges reflect asset allocation decisions of fund investors, in contrast to sales net of redemptions which incorporate long term savings and withdrawals. If SAD indeed impacts investor asset allocation decisions then a clear implication of Ben-Rephael, Kandel, and Wohl's (2010a) claim is that this impact should be

Time Series of Net Flows:
Corporate Fixed Income and Government Fixed Income

Panel A — Corporate Fixed Income | Panel B — Government Fixed Income

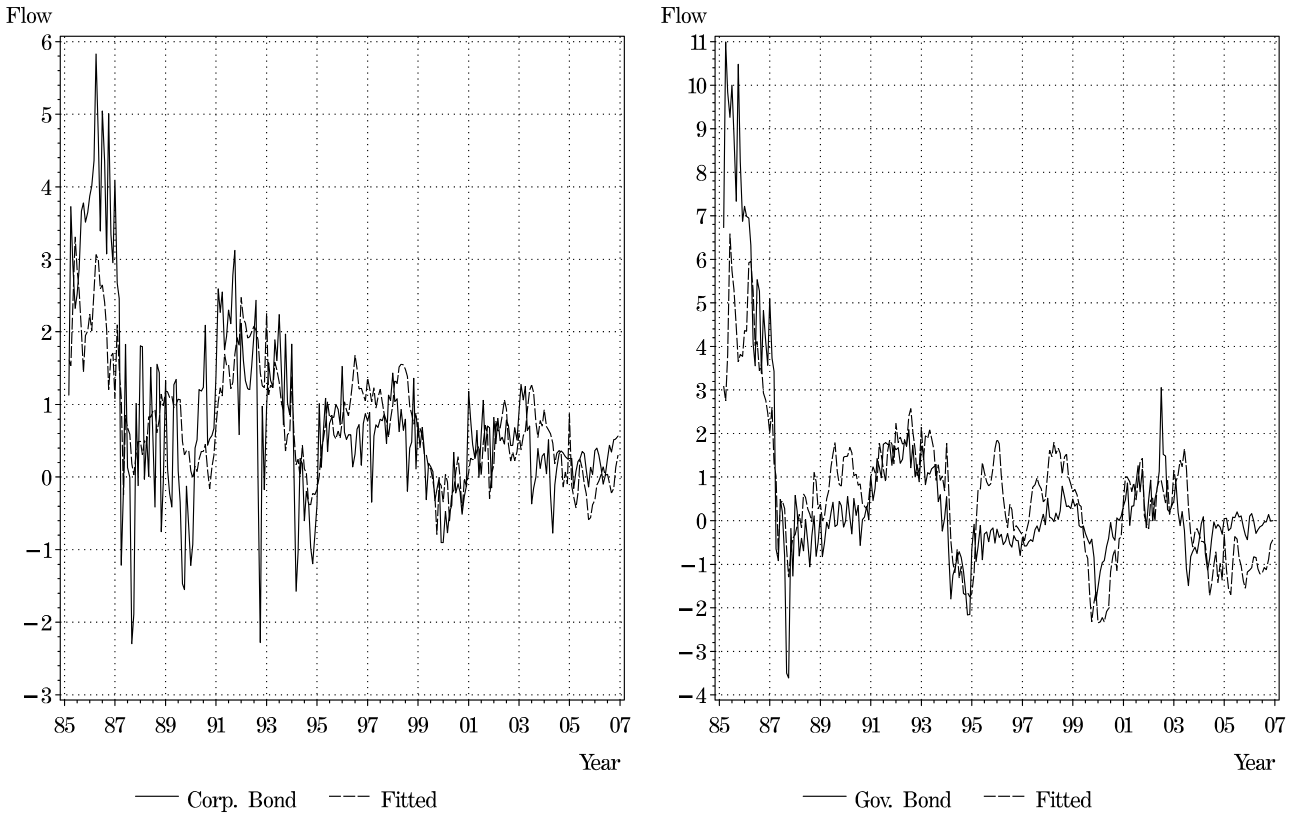

Figure 6: Panel A contains the time series of monthly **corporate fixed income** fund net flows as a proportion of corporate fixed income class TNA, indicated with a solid line, and the time series of monthly fitted values from estimating Equation (1), indicated with a dashed line. Panel B contains the time series of monthly **government fixed income** fund net flows as a proportion of government fixed income class TNA, indicated with a solid line, the time series of monthly fitted values from estimating Equation (1), indicated with a dashed line. The data, provided by the Investment Company Institute, span January 1985 through December 2006.

evident in net exchanges.

The regression model we consider for net exchanges is:

$$NetExchange_{i,t} = \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} + \epsilon_{i,t}, \qquad (2)$$

where i references the mutual fund asset class. The dependent variable, $NetExchange_{i,t}$, is now the month t net exchange expressed as a proportion of month $t-1$ total net assets, and the remaining variables are as previously defined. In this model we exclude personal savings, as exchanges between funds should be invariant to this quantity; indeed a point of looking at net exchanges is to expunge the impact of savings directly rather than simply control for it in the regression model.

We estimate Equation (2) as a system of equations using Hansen's (1982) GMM and Newey and West

Time Series of Net Flows: Money Market

Panel A
Money Market

Panel B
Money Market

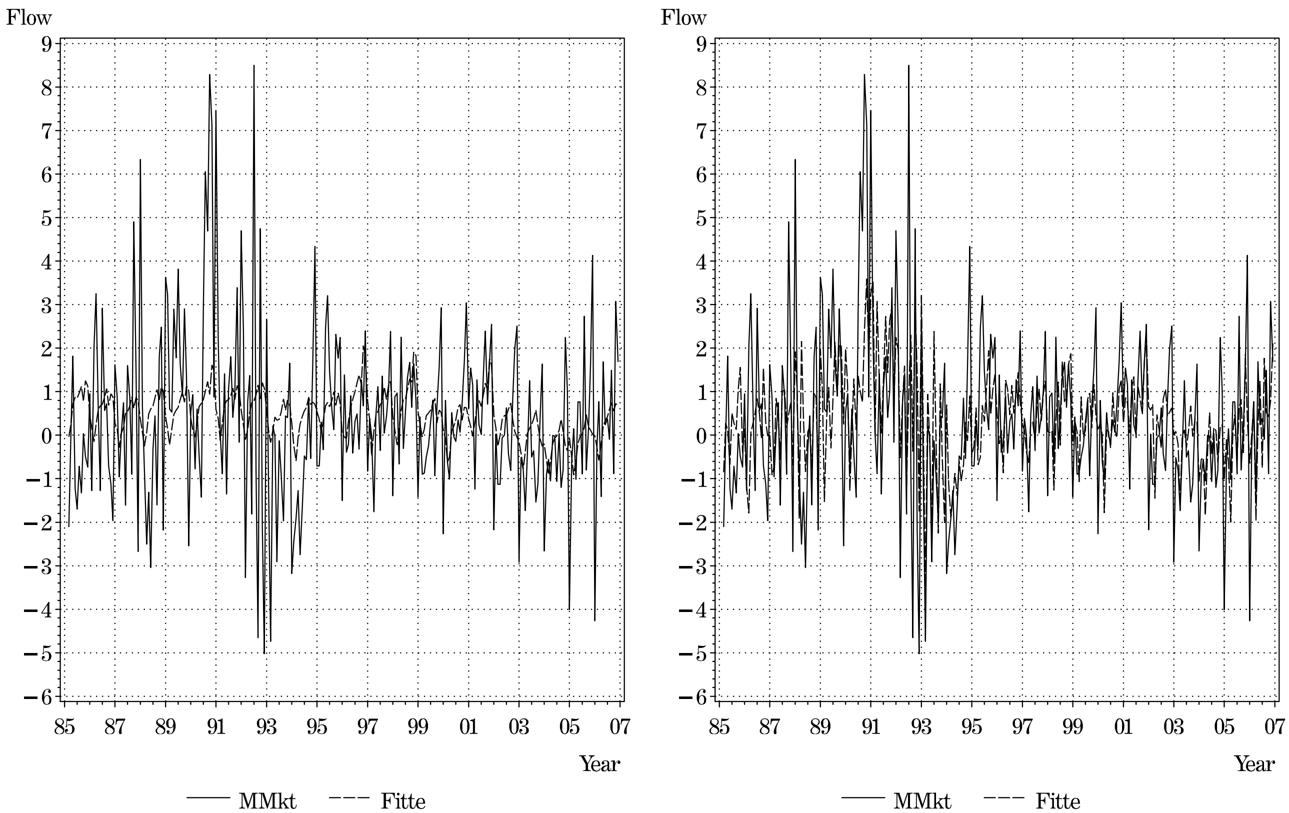

Figure 7: Panel A contains the time series of monthly **money market** fund net flows as a proportion of money market class TNA, indicated with a solid line, and the time series of monthly fitted values from estimating Equation (1), indicated with a dashed line. Panel B contains the time series of monthly **money market** fund net flows as a proportion of money market class TNA, indicated with a solid line, and the time series of monthly fitted values from estimating Equation (3), indicated with a dashed line. The data, provided by the Investment Company Institute, span January 1985 through December 2006.

(1987) HAC standard errors. Results from estimating this set of equations are shown in Table 5. In Panel A we present coefficient estimates and two-sided t-tests. The bottom of Panel A contains adjusted R^2 for each asset class model and χ^2 statistics for testing for the presence of up to 12 lags of autocorrelation (AR) or ARCH.

Similar to the results presented for net flows, the $\hat{OR}_t$ estimated coefficients for net exchanges are insignificant for the hybrid, corporate, and government fixed income asset classes, negative and significant for the equity class, and positive and significant for the money market class. Again the money market class displays the largest economic magnitude effect. The statistics in Panel B reveal that the onset/recovery estimates are jointly statistically different from zero and different from each other across asset classes, again strongly rejecting the null of no SAD-related seasonal effect. The goodness-of-fit test indicates that the over-identifying moment restrictions we use estimate the model are not rejected.

5.4 Economic Magnitude

One way to assess the economic impact of the influence of SAD on net flows and net exchanges is directly from our $\hat{OR}$ coefficient estimates. For example in Table 4 (based on net flows), the $\hat{OR}$ coefficient estimate is 1.3 for the money market class. To calculate economic impact, we multiply 1.3 by the value of the onset/recovery variable for a given month. In September, onset/recovery equals 38 percent (as reported in Section 2). Thus the average economic impact of SAD on money market fund flows in the month of September is roughly 50 basis points of the total net assets of the taxable government money market class.

Another way to assess the economic magnitude is by calculating the actual dollar flows associated with the impact of SAD. For example, in September 2005, total net assets of the taxable government money market class was 353 billion dollars. Multiplying that value by the 50 basis points of TNA we calculated above yields a SAD-associated economic impact of over 1.7 billion dollars flowing into the money market asset class in September 2004. In the spring, the economic impact was such that about 1.9 billion dollars flowed out of money market funds in March 2005. For the equity class, over 10 billion dollars of SAD-associated flows occurred during March 2004, and over 8 billion dollars flowed out during September 2004.

In Figure 8 we summarize the economic impact for all five asset classes, averaged across all years in our sample. Each line represents the average monthly economic magnitude of the SAD effect for a given fund. The thick dotted line that varies oppositely to the remaining lines corresponds to the money market. That asset class has experienced average outflows due to SAD exceeding 1.5 billion dollars in the spring and inflows exceeding 1.5 billion dollars in the fall. The equity class, represented by a thinner dotted line, has experienced average outflows due to SAD of over 4 billion dollars in the fall and inflows over 4 billion dollars in the spring. Other asset classes have exhibited less extreme flows due to SAD than the riskiest and safest fund categories.

If we aggregate the monthly economic magnitude across all categories, it is apparent that the SAD-associated mutual fund flows do not net out perfectly to zero across our categories, so there must be some other counterbalancing category of savings from which and to which funds flow. When aggregated across all fund categories, the net flows attributable to SAD show outflows in the fall and inflows in the winter, about $5 billion per month at their monthly maximum. This is not an artifact of a particular model specification, but a very robust feature of the data. The aggregated net exchanges are smaller in magnitude, but similarly proportionally unbalanced.

Flows Attributed to SAD, in Billions of Dollars

Panel A — Net Flows; Panel B — Net Exchanges

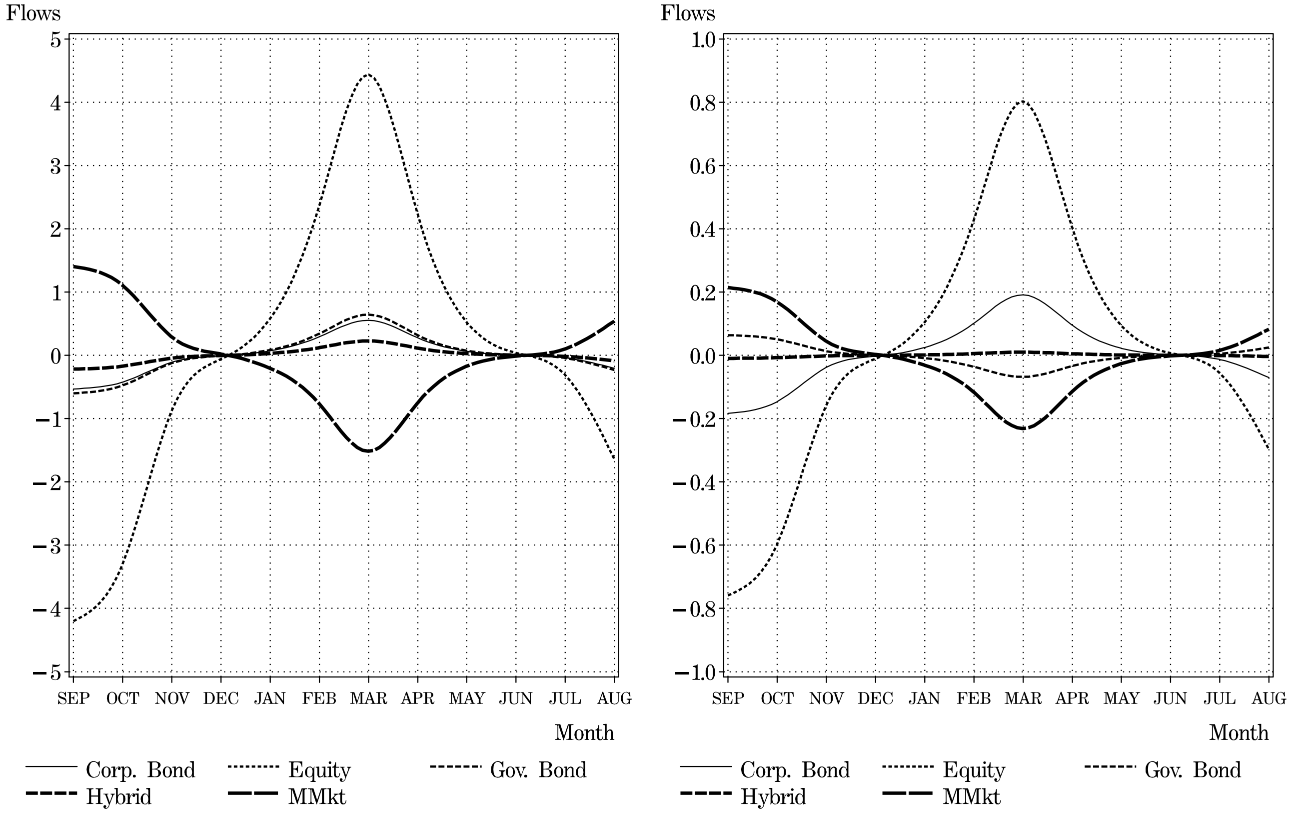

Figure 8: This figure contains the average monthly flows due to SAD, in billions of dollars, by fund asset-class. The legend indicates which lines represent which classes. The data underlying the averages, provided by the Investment Company Institute, span January 1985 through December 2006. Panel A presents total net flows, and Panel B presents net exchanges.

Of course there are many other places money flows to and from. The largest is, perhaps, bank accounts, including checking, savings, and money market accounts (separate and distinct from money market mutual funds). We considered deposit data (seasonally unadjusted and adjusted for inflation) provided by the Board of Governors of the Federal Reserve System.[20] We found that bank accounts did indeed have inflows and outflows that match the direction of money market fund flows: inflows in the fall and outflows in the winter. The winter outflows average to just over 4 billion dollars, a good match to the unaccounted-for fund flows, but the fall bank account inflows are large, at roughly 19 billion dollars per month. Some of these flows are likely an artifact of saving in advance of holiday spending, and saving does peak late in the quarter. If we leave out the December buildup in deposits we have an average monthly increase of approximately 10 billion dollars.

[20] We obtained total savings deposits and demand deposits plus other checkable deposits, from the St. Louis Federal Reserve Bank, series IDs SAVINGNS and TCDNS respectively, deflated with CPIAUCNS (the consumer price index for all urban consumers, seasonally unadjusted, from the US Department of Labor: Bureau of Labor Statistics).

5.5 Autocorrelation in Money Market Fund Flows

We see from our regression results in Table 4 that there is considerable autocorrelation in the regression residuals, and although we exploit HAC standard errors, it is helpful to estimate a model that incorporates lags of the dependent variable to directly control for autocorrelation. (This model was mentioned above in reference to the diamond-marked line in Panel B of Figure 4.) Specifically, we include one-month, three-month, six-month, and twelve-month lags of the dependent variable as additional regressors. The model we estimate is as follows:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \mu_{i,Savings}Savings_{i,t} + \rho_1 NetFlow_{i,t-1} + \rho_3 NetFlow_{i,t-3} \\ &+ \rho_6 NetFlow_{i,t-6} + +\rho_{12} NetFlow_{i,t-12} + \epsilon_{i,t}. \end{aligned} \quad (3)$$

We estimate Equation (3) as a system of equations using GMM and HAC standard errors. Results appear in Table 6. Note that there remains no significant evidence of autocorrelation in the residuals, and very little evidence of ARCH. Otherwise, our findings are qualitatively similar to those discussed above, with a negative and significant coefficient estimates on the onset/recovery variable for the equity, hybrid, and corporate fixed income flows and a positive and significant coefficient estimate for money market flows. As before, joint tests support the position that the safe and risky fund flows exhibit opposing seasonal cycles related to the onset/recovery variable.

6 Australian Flows

In this section, we test whether the relation of mutual fund flows to seasonal depression is similar in a different financial market, controlling for calendar effects. For instance, we would like to rule out the minimize the possibility that our result arises due to the influence of particular calendar months, perhaps as a result of a “turn-of-the-year” effect or a tax-timing effect. To do so, we now consider a developed market in the Southern Hemisphere, where the relation between the calendar and the seasons is offset by six months relative to North America.

Specifically, we examine flows to/from Australian-domiciled equity funds that invest in Australian equities, with the assumption that the majority of flows to these funds come from individuals domiciled in Australia. These individual investors are confronted with a SAD effect that is the inverse of the SAD cycle in North America. In Australia, the summer solstice occurs in December, while the winter solstice occurs in June; this helps us to see whether SAD affects flows, independent of the actual calendar month.

We obtained end-of-month total net assets (TNA) and estimated flows from Morningstar for all Australian-domiciled mutual funds with an Australian equity focus for the period January 1991 to December 2006.[21] The need for lagged values restricts the range of data we use in our regression model to start in January 1992. We are not able to obtain data on Australian government money market funds from Morningstar, so we proceed with an analysis that focuses solely on equity funds. To minimize the influence of any potential data errors or outliers, we eliminate all fund-month observations having a flow (inflow or outflow) greater (in absolute value) than 10% of the prior month-end TNA (such data points are rare, constituting only 0.15% of our sample of fund-months).

Our sample consists of 91 funds with a total market value of 1.6 billion Australian dollars (AUD) on January 1, 1991 (which translates into roughly 1.2 billion US dollars, USD, at that date) , growing to 599 funds with a total market value of 70.2 billion AUD by December 31, 2006 (about 55.3 billion USD at that date). This market is roughly 1% the size (in value) of the US equity mutual fund market as of December 31, 2006.

In Figure 9 we consider seasonal patterns in investor fund flows associated with these Australian equity funds. Consider first Panel A, in which the solid line corresponds to the monthly average flows. The unconditional seasonal patterns in equity fund flows are consistent with SAD having an impact on flows, and a pattern that is the reverse of US equity fund flows. We see equity fund net inflows are lower than average during most of the Australian fall and early winter (autumn officially begins in March in the Southern Hemisphere) and are higher than average during most of the Australian late winter and spring. This is similar to US equity fund flows but six months out-of-phase. Overall, the lower-than-average flows in the fall and higher-than-average flows in the late winter/spring are consistent with SAD-affected investors shifting their portfolios out of risky funds coinciding in time with their seasonally declining risk aversion, and doing so six months later than in the US. The light dotted lines surrounding the solid line (the monthly average flows) are the 90% confidence interval around the monthly flows. Unlike the US flow data, the evidence shows little statistically significant unconditional seasonality, with only 4 months exhibiting significant evidence of monthly seasonality. [22]

[21] Although earlier data are available, the number of funds in the database is below 100 prior to 1991.

[22] We believe that the flows in June and July (and possibly May as well) are largely related to end-of-tax-year effects, as the Australian tax year ends in June.

The *time-series* fit of the model is shown in Panel B. The flows and the model fit are relatively consistent over the sample, with the largest oscillations occuring around the end of the tax year, and the fit of the model being the worst at (and around) the tax-year-end, implying that this oscillation has little to do with the SAD effect or autocorrelation in flows.

Australian Net Flows

Panel A Monthly Averages | Panel B Time Series

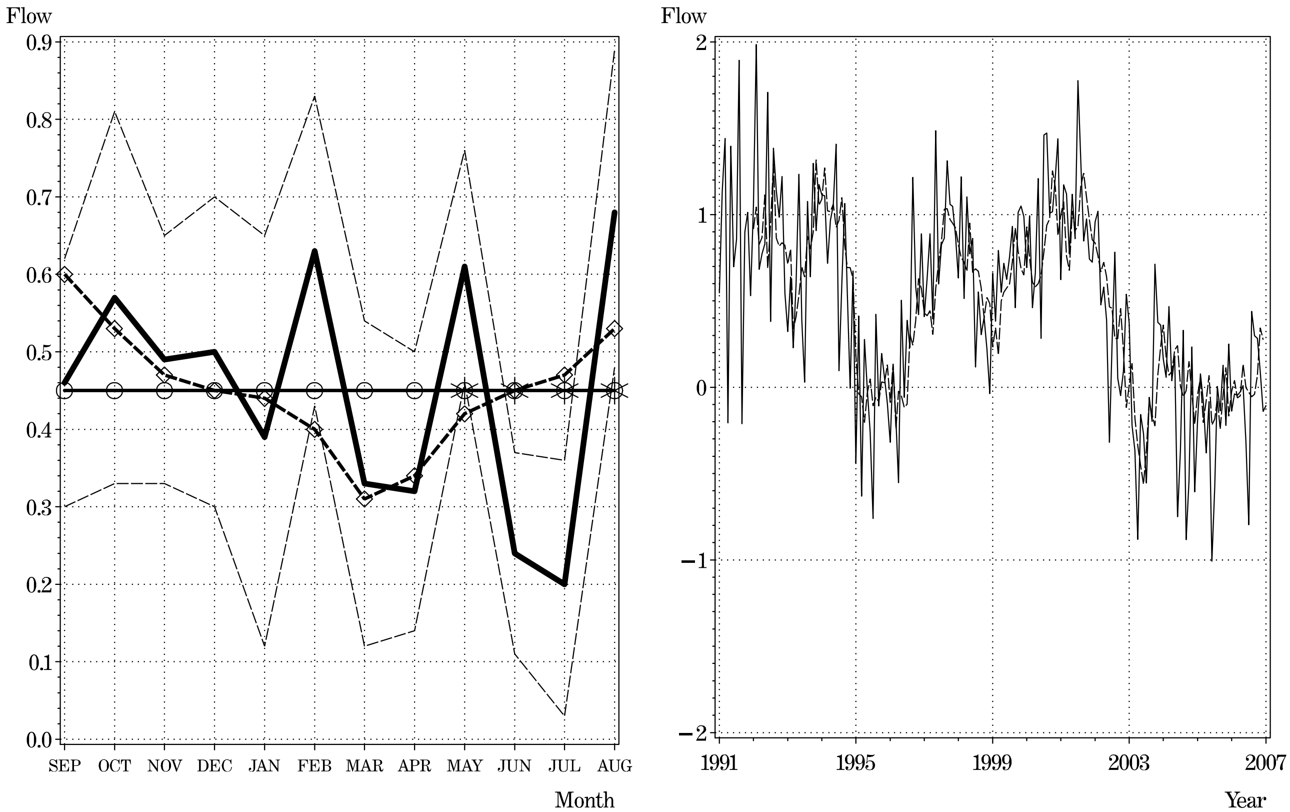

Figure 9: Panel A contains monthly average **Australian equity** aggregate fund flows as a proportion of Australian equity fund TNA, indicated with a solid line, and average fitted values implied by the Southern Hemisphere onset/recovery coefficient from estimating Equation (4), indicated with a dashed line with diamonds. Panel A also includes a 90% confidence interval around the monthly means (shown with light dashed lines) and the average flow throughout the year (represented by a solid line with circles – and an x mark in cases where the average return falls outside of the confidence interval). Panel B contains the time series of monthly **equity** aggregate fund flows as a proportion of equity TNA, indicated with a solid line, the monthly fitted values from estimating Equation (4), indicated with a dashed line.

Next we turn to conditional analysis of the Australian data. The regression model we consider is:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}_{South}} \hat{OR}_{South_t} + \mu_{i,R^{Year}} R^{Year}_{i,t} + \rho_1 NetFlow_{i,t-1} \\ &+ \rho_3 NetFlow_{i,t-3} + \rho_6 NetFlow_{i,t-6} + \rho_{12} NetFlow_{i,t-12} + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where i references the mutual fund asset class. The dependent variable, $NetFlow_{i,t}$, is the month t aggregate fund flow expressed as a proportion of month $t-1$ total net assets. $\hat{OR}_{South_t}$ is the SAD onset/recovery variable, offset by six months from its US counterpart to align with the Southern Hemisphere seasons, and $R_{i,t}^{Year}$ is the return to fund asset class i over the prior 12 months (*i.e.,* from month $t-13$ through month $t-1$), included to control for return-chasing flows. Unfortunately we are not able to obtain savings-rate data, advertising data, or capital gains proxies for the Australian data.

This model, while simpler than that estimated for US flows, still explains much of the variation in fund flows, with an R^2 exceeding 57%. The residuals show no statistically significant evidence of autocorrelation or ARCH effects, and like fund flows in the US, unadjusted equity fund flows in Australia show strong positive autocorrelation. Similar to the SAD effect for US equities, the sign of the SAD onset/recovery variable is negative (recall that we are using a Southern Hemisphere version of the SAD variable, so that we expect it to have the same sign for equity funds in Australia as we saw for equity funds in the US). Further, the magnitude is economically meaningful: the coefficient value of -.371 corresponds to a 37 basis point impact per unit of the SAD variable and the SAD variable varies between roughly plus and minus .4. This translates into roughly 15 basis points of variation in either direction, which aggregates to a total of 30 basis points of variation in flows associated with SAD. We also find strong evidence of return chasing, with lagged returns positively and statistically significantly inflating flows. While the impact of a unit change in the SAD variable is lower in Australia than in the US (30 vs. 60 basis points), we note that a simple inversion of our US SAD variable may not precisely capture how SAD influences individuals in Australia.

In Figure 10, we summarize the average economic impact from flows associated with SAD for Australian equity funds, averaged across all years in our sample, with the thin solid line representing SAD flows. Naturally these flows are much smaller in magnitude than the corresponding flows for the US, ranging between outflows and inflows of approximately 35 million AUD (roughly 28 billion USD during our time range).

7 Robustness of Results

7.1 Redefining Asset Classes

As a supplement to studying the five asset classes, we explored a less coarse classification of the 33 ICI fund categories. In Table 7 we map the 33 ICI categories into nine asset classes, allowing more variation in risk across the classes. Instead of "equity", we now consider "risky equity" and "safe equity." "Hybrid" remains as previously defined. "Corporate fixed income" is split into "global bond" and "corporate bond".

Australian Flows Attributed to SAD, in Billions of AUD

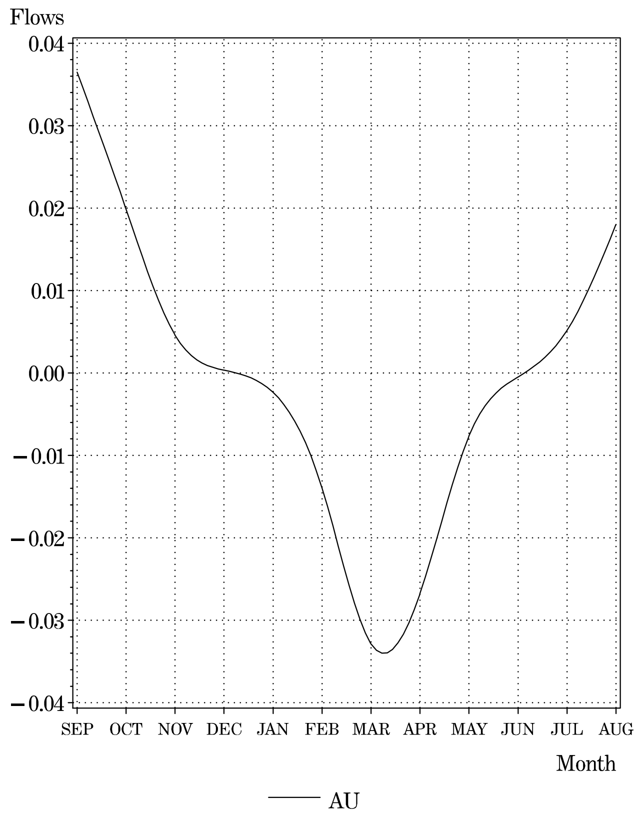

Figure 10: This figure reports the average monthly flows due to SAD, in billions of AUD, for equity funds. The data on equity fund flows, provided by Morningstar span January 1992 through December 2006.

"Government fixed income" is split into "munis," "medium and short-term government," and "general-term government." The "money market" class remains as previously defined. Summary statistics on these nine classes are presented in Table 8.

In Table 9 we present results from estimating Equation (1) as a system of nine equations (across the expanded set of nine asset classes) using GMM and HAC standard errors. Panels A and B contain coefficient estimates and some regression diagnostic statistics, and Panel C contains joint test statistics across the classes.

We find the onset/recovery variable coefficient estimate is negative and significant for the risky equity, safe equity, hybrid, and US corporate bond asset classes. We find a positive and significant coefficient estimate for the global corporate bond and money market classes. Joint tests in Panel C support the notion that the safest and riskiest fund flows exhibit opposing seasonal cycles related to SAD and that the onset/recovery estimates are jointly statistically different from zero, again strongly rejecting the null of no SAD-related seasonal effect.

7.2 Additional Robustness Checks

We conducted a variety of additional robustness tests. First, in a previous version of this paper, we found very similar results based on risky and safe categories of mutual funds found in the CRSP Mutual Fund Database. Second, as reported in the previous section, we find virtually identical results when we exclude the first few years or the first half of our sample. Third, ICI implemented some data collection changes in January 1990, producing outlier data for flows and returns. As a result we explored dummying out 1990 altogether. This produced no qualitative changes in our results. Fourth, we imposed a moment condition on SAD flows so that that the total impact of SAD would net out to zero. This tightened standard errors, but otherwise did not produce notable changes to our estimation.

Finally, we explored a number of alternatives to our proxy for capital gains overhang. These proxies are based on either the ICI cumulated changes in TNA, adjusted for inflows, or actual capital gains recorded by funds and collected through the CRSP Mutual Fund Database. In each case we accumulate capital gains for year t from the the previous year $t-1$ November (as the end-of-year for mutual funds is October). The value of the proxy for November and December in each and every case is the accumulated gains from the previous year's November to the current year's October. Depending on which proxy we are employing in a particular model, the value of the proxy for January though October is either zero (as we expect the impact on flows of capital gains to be muted before end-of-year) or the accumulated capital gains from the previous year's November to the month in question.[23] We develop two capital gain measures using ICI data: a simple measure equal to the change in TNA, adjusted for inflows, and and this simple measure less all distributions (as distributions tend to not include capital gains). From each of these two capital gains measures, we form two accumulated capital gains overhang proxy variables, one with accumulated gains January through October, and one set to zero January through October, yielding four alternative measures based on the ICI data. From the CRSP Mutual Fund capital gains data we also form accumulated capital gains overhang proxy variables in these two alternative ways, one with accumulated

[23] When calculating capital gains overhang proxies, we assume that for November and December the gains to be taxed are known by investors and do not need to be forecasted by investors. Note, however, that the proxy is measured contemporaneously with the flow, and this endogeneity must be accounted for. Hence we use past (known) capital gains accumulated plus a forecast for the current month, January through October. As a result, our capital gains overhang proxies that include gains for each month of the year integrate predicted capital gains to avoid endogeneity. Specifically, we construct predicted capital gains by regressing our capital gains proxy on 12 monthly dummy variables (excluding the intercept to avoid perfect multicollinearity) and 12 lags of the proxy. The January through October values are the accumulated actual capital gains (price appreciation plus all distributions) from November of the previous year through to the month immediately preceding a given month (so that we do not use contemporaneous unknown capital gains) plus the predicted capital gains for that month. The November and December values are the current year's October value of the accumulated capital gains.

gains January through October, and the other with the overhang variable set to zero for January through October. Additionally, the bond and money market funds tend to distribute gains throughout the year and have less price appreciation, so that the simple capital gains overhang proxy built on the change in TNA adjusted for inflows is most appropriate, but arguably the equity funds exhibit capital gains that are best approximated by the simple measure less all distributions. So we also explore a mix-and-match set of capital gains overhang proxies across our series based on the ICI data rather than imposing the same proxy construction across series, constructing the bond and money market fund capital gains overhang proxy with the change in TNA, adjusted for inflows, and the equity funds overhang proxy with the simple measure less all distributions. Altogether this came to seven alternative capital gains overhang proxies. We also explored a possible reversal of flows in January arising from the capital gains overhang effect. We did this by including a January dummy variable in each of the models that included a capital gains overhang proxy. Results based on these various robustness checks were qualitatively similar; in particular the SAD result was not disturbed.

8 Conclusion

In this paper, we have documented a seasonal pattern in mutual fund flows that is consistent with some individual investors becoming more risk averse in the fall, as the days shorten, and less risk averse in the spring, as the days lengthen; that is, consistent with these individuals experiencing changes in risk aversion due to seasonal depression. SAD is a seasonal form of depression that affects up to ten percent of the population severely and up to an additional thirty percent sub-clinically, with those affected experiencing depression and risk aversion that increase with the length of night. While prior studies have found economically and statistically significant evidence of a systematic influence of SAD on stock and Treasury bond returns, our study is the first to directly link the seasonal cycles of SAD to seasonal patterns in mutual fund flows.

Specifically, we find that flows to the riskiest group of mutual funds, equities, are lower in the fall and higher in the spring, while flows to the safest category, money market funds, exhibit the opposite pattern. We find that these seasonal patterns are significantly related to the SAD onset/recovery variable, after controlling for other prior-documented influences on flows including past returns, advertising, and capital-gains distributions. Further, the significant explanatory power of the SAD onset/recovery variable remains when we add sufficient lags to our models to control for autocorrelation, indicating that the SAD variable is not picking up simple lead-lag effects in unexpected flows. The evidence for SAD-related seasonality survives subsample analysis, finer granularity of analysis of fund class, alternative measures of capital gains, and application to net exchanges, a measure of investor sentiment studied by Ben-Rephael, Kandel, and Wohl (2010a, 2010b).

The seasonal flows associated with SAD are economically large, representing billions of dollars. These large flows are consistent with the SAD-related stock and bond returns documented by Kamstra, Kramer, and Levi (2003, 2010) and Garrett, Kamstra, and Kramer (2005). Further research is needed to investigate whether trades by funds due to SAD flows impact stock and bond returns. In addition, future research might investigate the trading behavior of individuals, using brokerage datasets, to study SAD-related behavior on a micro level.

Finally, it is noteworthy that the mutual fund industry spends more than half a billion dollars per year on advertising. Our findings suggest that the impact of this advertising may largely divert flows rather than create new flows, and in any case the industry might 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.

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Table 1: Seasonality in Capital Gain and Dividend Distributions to Mutual Fund Shareholders

This table presents seasonal patterns in capital gains and dividend distributions among all mutual funds over the 1984 to 2007 period. To compute the frequency of capital gains distributions during a given month, we first eliminate capital gains distributions that are a return of capital (i.e., are non-taxable). Then, we divide the number of capital gains distributions occurring during that month (across all years) by the total number of capital gains distributions across all months. Panel A presents these frequencies, while Panel B presents results computed for dividend distributions. For dividend distributions, we exclude all non-taxable distributions, such as the tax-exempt portion of dividends distributed by municipal bond funds.

Panel A: Taxable Capital Gains Distribution Frequency (%)
(Percent of Number of Distributions, 1984-2007)

Month	Percent
January	1.1
February	0.9
March	2.4
April	1.1
May	1.5
June	3.8
July	1.9
August	1.8
September	2.2
October	1.6
November	9.8
December	72.0

Panel B: Taxable Dividend Distribution Frequency (%)
(Percent of Number of Distributions, 1984-2007)

Month	Percent
January	6.9
February	7.0
March	8.9
April	7.3
May	7.2
June	9.3
July	7.5
August	7.3
September	9.3
October	7.7
November	7.6
December	14.1

Table 2: Classification of Funds

The Investment Company Institute uses 33 categories to classify funds by investment objective. In this table we map funds from those investment objective categories into a smaller set of five asset classes, based on characteristics of the individual funds provided in the Investment Company Institute (2003) Mutual Fund Factbook. The classes are "Equity," "Hybrid," "Corporate Fixed Income," "Government Fixed Income," and "Money Market."

Fund Number	ICI Fund	Asset Class
1	Aggressive Growth	Equity
2	Growth	Equity
3	Sector	Equity
4	Emerging Markets	Equity
5	Global Equity	Equity
6	International Equity	Equity
7	Regional Equity	Equity
8	Growth and Income	Equity
9	Income Equity	Equity
10	Asset Allocation	Hybrid
11	Balanced	Hybrid
12	Flexible Portfolio	Hybrid
13	Income Mixed	Hybrid
14	Corporate - General	Corporate Fixed Income
15	Corporate - Intermediate	Corporate Fixed Income
16	Corporate - Short Term	Corporate Fixed Income
17	High Yield	Corporate Fixed Income
18	Global Bond - General	Corporate Fixed Income
19	Global Bond - Short Term	Corporate Fixed Income
20	Other World Bond	Corporate Fixed Income
21	Government Bond - General	Government Fixed Income
22	Government Bond - Intermediate	Government Fixed Income
23	Government Bond - Short Term	Government Fixed Income
24	Mortgage Backed	Government Fixed Income
25	Strategic Income	Corporate Fixed Income
26	State Municipal Bond - General	Government Fixed Income
27	State Municipal Bond - Short Term	Government Fixed Income
28	National Municipal Bond - General	Government Fixed Income
29	National Municipal Bond - Short Term	Government Fixed Income
30	Taxable Money Market - Government	Money Market

Table 3: Summary Statistics on Monthly Percentage Asset Class Net Fund Flows, Net Exchanges, Explanatory Variables, and Associated Returns to Holding These Funds

In this table we present summary statistics on monthly fund net flows, net exchanges, explanatory variables, and returns over January 1985 through December 2006, for a total of 263 months. Flows data are from the Investment Company Institute, and returns were calculated using fund flow and total net asset changes available from the Investment Company Institute. The returns are in excess of the 30-day T-bill rate, available from CRSP. $R^{CapGains}$ is our capital gains proxy based on cumulated fund percentage returns for November and December, and R^{Year} is the one-year moving average of fund percentage returns, to capture return chasing. Savings are based on real disposable income and expenditures as a percent of real disposable income, annualized. For each set of fund flows and returns we present the mean monthly values (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew) and kurtosis (Kurt). For excess returns we also present the CAPM beta and the coefficient estimate on the SAD onset variable, each estimated separately of the other. These coefficients are produced in a systems equation estimation using GMM and heteroskedasticity and autocorrelation consistent standard errors. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. The instruments used for the CAPM regression are the market return, a constant, and one lag of each excess return. The instruments used for the SAD regression are the onset variable, a constant, and one lag of each excess return.

Panel A: Asset Class Net Flows

Index	Mean	Std	Min	Max	Skew	Kurt
Equity	0.591	0.82	-3.17	3.82	0.009	2.27
Hybrid	0.795	1.36	-1.68	6.67	1.157	1.47
Corporate Fixed Income	0.787	1.26	-2.29	5.83	1.123	2.20
Government Fixed Income	0.653	2.22	-3.62	10.99	2.549	7.22
Money Market	0.378	2.01	-5.02	8.50	0.797	2.48

Panel B: Asset Class Net Exchanges

Index	Mean	Std	Min	Max	Skew	Kurt
Equity	-0.040	0.34	-2.65	1.06	-2.554	16.19
Hybrid	-0.048	0.22	-0.82	0.75	-0.014	2.50
Corporate Fixed Income	-0.031	0.43	-2.67	1.23	-1.736	9.08
Government Fixed Income	-0.083	0.32	-2.22	1.35	-1.422	9.90
Money Market	0.070	0.38	-0.85	3.59	4.237	31.11

Table 3 continues on next page

Table 3, Continued

Panel C: Explanatory Variables

Index	Mean	Std	Min	Max	Skew	Kurt
Advertising	1.009	0.19	0.53	1.72	0.625	0.36
Savings	1.534	0.11	1.30	1.90	0.323	0.04
Equity Fund Specific:						
$R^{CapGains}$	2.370	8.08	-29.52	45.85	2.039	9.21
R^{Year}	1.178	1.22	-2.95	3.82	-0.957	0.87
Hybrid Fund Specific:						
$R^{CapGains}$	1.657	5.05	-6.90	25.82	2.879	8.52
R^{Year}	0.826	0.69	-0.98	2.22	-0.276	-0.49
Corporate Fixed Income Fund Specific:						
$R^{CapGains}$	1.578	4.45	-4.28	20.44	2.648	6.04
R^{Year}	0.786	0.52	-0.46	2.01	-0.150	-0.58
Government Fixed Income Fund Specific:						
$R^{CapGains}$	0.951	3.00	-4.57	17.20	3.058	10.30
R^{Year}	0.482	0.43	-0.47	1.88	0.496	0.95
Money Market Fund Specific:						
$R^{CapGains}$	1.008	3.00	-3.37	15.29	2.987	9.06
R^{Year}	0.508	0.37	-0.44	1.40	-0.470	0.33

Panel D: Fund Excess Returns

Index	Mean	Std	Min	Max	Skew	Kurt	Beta	SAD
Equity	0.781	4.20	-20.85	19.09	-0.726	4.19	0.919***	-1.271*
Hybrid	0.434	2.51	-10.80	8.44	-0.767	2.27	0.502***	-.7125
Corporate Fixed Income	0.396	1.30	-2.91	6.65	0.298	1.59	0.118***	0.1105
Government Fixed Income	0.068	1.09	-3.65	3.55	-0.258	0.71	0.023*	0.6944***
Money Market	0.125	0.91	-2.75	5.98	1.317	7.74	-0.000	0.3142**

Table 4: Regression Results for Asset Class Net Flows

In this table we report coefficient estimates from jointly estimating the following regression for each of the fund asset classes in a GMM framework:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{Ads}Ads_t + \mu_{i,R^{Year}}R_{i,t}^{Year} + \mu_{i,CapGains}R_{i,t}^{CapGains} \\ &+ \mu_{i,Savings}Savings_{i,t} + \epsilon_{i,t}. \end{aligned} \quad (1)$$

The data span January 1985 through December 2006. The monthly net flows are computed as sales, minus redemptions, plus exchanges in, minus exchanges out. The dependent variable is monthly fund net flows as a proportion of the previous month's TNA. The explanatory variables are defined in the text. 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 adjusted R^2 for each estimation, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test statistic for the presence of up to 12 lags of ARCH (both with 12 degrees of freedom). The test for ARCH is a standard LM test of order 12. See Engle (1982). To perform the test for autocorrelation, we augment our regression with 12 lags of the residuals, estimate MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors with OLS and test for the joint significance of these terms. Panel B contains joint test statistics. The first is a χ^2 statistic (with 5 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly zero across the asset classes, the second is a χ^2 statistic (with 4 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly equal to each other across the asset classes, and the third is the Hansen (1982) χ^2 goodness-of-fit test of our model based on the optimized value of the objective function produced by GMM. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$ The instruments used for the regression are the explanatory variables. 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 and Diagnostic Statistics

Parameter or Statistic	Equity	Hybrid	Corporate Fixed Income	Government Fixed Income	Money Market
μ	-1.675***	-6.063***	-5.935***	-7.651***	-0.406
	(-3.84)	(-7.74)	(-6.29)	(-5.22)	(-0.38)
$\mu_{\hat{OR}}$	-0.600***	-0.256	-0.464	-0.404	1.297***
	(-2.96)	(-0.68)	(-1.62)	(-0.97)	(2.95)
μ_{Ads}	0.039	-0.289	-0.757***	-0.502	-0.646*
	(0.21)	(-0.98)	(-2.94)	(-1.13)	(-1.69)
μ_{Year}	0.213***	0.661***	0.951***	2.889***	0.560***
	(7.16)	(7.10)	(8.98)	(10.07)	(2.74)
$\mu_{Savings}$	1.284***	4.287***	4.402***	4.852***	0.759
	(5.05)	(8.46)	(7.72)	(5.43)	(1.13)
$\mu_{CapGains}$	-0.003	-0.009	-0.015*	-0.044**	0.073***
	(-1.00)	(-1.03)	(-1.87)	(-2.09)	(3.24)
R^2	0.1743	0.3006	0.4446	0.5912	0.0613
AR(12)	184.69***	335.46***	115.52***	250.14***	55.47***
ARCH(12)	63.93***	68.74***	40.27***	67.32***	52.75***

Panel B: Joint Tests on Onset/Recovery Coefficient Estimates

Joint Test Across Asset Classes	χ^2 [Degrees of Freedom]
$\hat{OR}$ jointly equal to zero across asset classes	27.0*** [5]
$\hat{OR}$ jointly equal across asset classes	25.4*** [4]
Test of Over-Identifying Restrictions	41.9 [40]

Table 5: Regression Results for Asset Class Net Exchanges

In this table we report coefficient estimates from jointly estimating the following regression for each of the asset classes in a GMM framework:

$$NetExchange_{i,t} \quad = \quad \mu_i + \mu_{i,\hat{OR}} \hat{OR}_t + \mu_{Ads} Ads_t + \mu_{i,R^{Year}} R_{i,t}^{Year} + \mu_{i,CapGains} R_{i,t}^{CapGains} + \epsilon_{i,t}. \tag{2}$$

The data span January 1985 through December 2006. The monthly net exchanges are computed as exchanges in minus exchanges out. The dependent variable is monthly fund net exchanges as a proportion of the previous month's TNA. The explanatory variables are defined in the text. 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 adjusted R^2 for each estimation, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test statistic for the presence of up to 12 lags of ARCH (both with 12 degrees of freedom). The test for ARCH is a standard LM test of order 12. See Engle (1982). To perform the test for autocorrelation, we augment our regression with 12 lags of the residuals, estimate MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors with OLS and test for the joint significance of these terms. Panel B contains joint test statistics. The first is a χ^2 statistic (with 5 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly zero across the fund asset classes, the second is a χ^2 statistic (with 4 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly equal to each other across the asset classes, and the third is the Hansen (1982) χ^2 goodness-of-fit test of our model based on the optimized value of the objective function produced by GMM. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. The instruments used for the regression are the explanatory variables. 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 and Diagnostic Statistics

Parameter or Statistic	Equity	Hybrid	Corporate Fixed Income	Government Fixed Income	Money Market
μ	0.054	-0.012	0.321***	0.045	-0.141**
	(0.78)	(-0.22)	(3.26)	(0.74)	(-2.02)
$\mu_{\hat{OR}}$	-0.109*	-0.011	-0.160	0.043	0.198**
	(-1.69)	(-0.16)	(-1.48)	(0.56)	(2.53)
μ_{Ads}	-0.101	-0.089*	-0.422***	-0.184***	0.195***
	(-1.45)	(-1.73)	(-4.12)	(-3.07)	(2.84)
μ_{Year}	0.007	0.055***	0.098***	0.145***	0.018
	(1.29)	(3.90)	(3.06)	(4.82)	(1.20)
$\mu_{CapGains}$	0.003***	0.002**	0.002	0.006**	-0.003**
	(4.15)	(2.29)	(0.84)	(2.51)	(-2.04)
R^2	0.0147	0.0506	0.0327	0.0644	0.0231
AR(12)	23.58**	256.08***	27.10***	34.19***	14.41
ARCH(12)	11.19	94.70***	17.85	32.34***	27.78***

Panel B: Joint Tests on Onset/Recovery Coefficient Estimates

Joint Test Across Fund Asset Classes	χ^2 [Degrees of Freedom]
$\hat{OR}$ jointly equal to zero across asset classes	15.0** [5]
$\hat{OR}$ jointly equal across asset classes	10.5** [4]
Test of Over-Identifying Restrictions	36.3 [40]

Table 6: Regression Results for Asset Class Net Flows Controlling Directly for Autocorrelation

In this table we report coefficient estimates from jointly estimating the following regression for each of the asset classes in a GMM framework:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \mu_{i,Savings}Savings_{i,t} + \rho_1 NetFlow_{i,t-1} + \rho_3 NetFlow_{i,t-3} \\ &+ \rho_6 NetFlow_{i,t-6} + +\rho_{12}NetFlow_{i,t-12} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

The data span January 1985 through December 2006. The monthly net flows are computed as sales, minus redemptions, plus exchanges in, minus exchanges out, all divided by the previous month's total net assets. The explanatory variables are defined in the text. 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 adjusted R^2 for each estimation, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test statistic for the presence of up to 12 lags of ARCH (both with 12 degrees of freedom). The test for ARCH is a standard LM test of order 12. See Engle (1982). To perform the test for autocorrelation, we augment our regression with 12 lags of the residuals, estimate MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors with OLS and test for the joint significance of these terms. Panel B contains joint test statistics. The first is a χ^2 statistic (with 5 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly zero across the asset classes, the second is a χ^2 statistic (with 4 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly equal to each other across the asset classes, and the third is the Hansen (1982) χ^2 goodness-of-fit test of our model based on the optimized value of the objective function produced by GMM. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. The instruments used for the regression are the explanatory variables. 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 and Diagnostic Statistics

Parameter or Statistic	Equity	Hybrid	Corporate Fixed Income	Government Fixed Income	Money Market
μ	-0.659***	-1.782***	-1.802***	-1.420***	2.212***
	(-4.83)	(-11.9)	(-8.24)	(-8.04)	(5.17)
$\mu_{\hat{OR}}$	-0.234***	-0.170***	-0.397***	-0.091*	1.189***
	(-4.91)	(-3.18)	(-6.16)	(-1.77)	(6.92)
$\mu_{Advertising}$	0.264***	0.151***	-0.531***	-0.137***	-0.991***
	(3.80)	(2.81)	(-6.71)	(-2.67)	(-5.42)
$\mu_{R^{Year}}$	0.011	0.034**	0.127***	0.015	0.041
	(1.35)	(2.34)	(4.03)	(0.40)	(0.40)
$\mu_{CapGains}$	0.005***	-0.002**	-0.013***	-0.032***	0.027**
	(4.85)	(-2.48)	(-4.79)	(-13.8)	(2.38)
$\mu_{Savings}$	0.330***	1.127***	1.630***	1.059***	-0.785***
	(4.46)	(11.99)	(12.64)	(9.32)	(-3.35)
ρ_1	0.426***	0.467***	0.485***	0.647***	0.089***
	(32.87)	(21.90)	(39.55)	(61.05)	(4.92)
ρ_3	0.294***	0.383***	0.275***	0.267***	0.323***
	(35.28)	(17.88)	(24.62)	(20.51)	(20.73)
ρ_6	-0.019*	-0.016	0.038***	0.068***	0.109***
	(-1.73)	(-1.34)	(3.27)	(4.96)	(6.88)
ρ_{12}	0.047***	-0.002	-0.112***	-0.087***	0.252***
	(5.61)	(-0.27)	(-11.7)	(-12.0)	(11.78)
R^2	0.4842	0.7041	0.6715	0.897	0.2989
AR(12)	21.18**	5.39	10.67	6.15	11.77
ARCH(12)	56.23***	68.43***	41.92***	48.56***	23.36**

Table 6 continues on next page

Table 6, Continued

Panel B: Joint Tests on Onset/Recovery Coefficient Estimates

Joint Test Across Asset Classes	χ^2 [Degrees of Freedom]
$\hat{OR}$ jointly equal to zero across sector funds	85.6*** [5]
$\hat{OR}$ jointly equal across sector funds	81.9*** [4]
Test of Over-Identifying Restrictions	47.5 [120]

Table 7: Classification of Funds into Enlarged Set of Nine Asset Classes

The Investment Company Institute uses 33 categories to classify funds by investment objective. In this table we map funds from those investment objective categories into a set of 9 asset classes, based on characteristics of the individual funds provided in the Investment Company Institute (2003) Mutual Fund Factbook. The asset classes are "Risky Equity," "Safe Equity," "Hybrid," "US Corporate Bond," "Global Corporate Bond," "General-Term Government," "Medium and Short-Term Government," "Munis," and "Money Market."

Number	ICI Fund	Asset Class (Based on Enlarged Set of 9)
1	Aggressive Growth	Risky Equity
2	Growth	Risky Equity
3	Sector	Risky Equity
4	Emerging Markets	Risky Equity
5	Global Equity	Safe Equity
6	International Equity	Safe Equity
7	Regional Equity	Safe Equity
8	Growth and Income	Safe Equity
9	Income Equity	Safe Equity
10	Asset Allocation	Hybrid
11	Balanced	Hybrid
12	Flexible Portfolio	Hybrid
13	Income Mixed	Hybrid
14	Corporate - General	US Corporate Bond
15	Corporate - Intermediate	US Corporate Bond
16	Corporate - Short Term	US Corporate Bond
17	High Yield	US Corporate Bond
18	Global Bond - General	Global Bond
19	Global Bond - Short Term	Global Bond
20	Other World Bond	Global Bond
21	Government Bond - General	General-Term Government
22	Government Bond - Intermediate	Medium and Short-Term Government
23	Government Bond - Short Term	Medium and Short-Term Government
24	Mortgage Backed	Medium and Short-Term Government
25	Strategic Income	US Corporate Bond
26	State Municipal Bond - General	Munis
27	State Municipal Bond - Short Term	Munis
28	National Municipal Bond - General	Munis
29	National Municipal Bond - Short Term	Munis
30	Taxable Money Market - Government	Money Market

Table 8: Summary Statistics on Monthly Percentage Flows for an Enlarged Set of Nine Asset Classes

In this table we present summary statistics on monthly fund flows, explanatory variables and returns over January 1985 through December 2006, for a total of 263 months for an enlarged set of nine asset classes. Flows data are from the Investment Company Institute, and returns were calculated using fund flow and total net asset changes available from the Investment Company Institute. The returns are in excess of the 30 day T-bill rate, available from CRSP. $R^{CapGains}$ is our capital gains proxy based on cumulated fund percentage returns for November and December, and R^{Year} is the one moving average of fund percentage returns, to capture return chasing. For each set of fund flows and returns we present the mean monthly values (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew) and kurtosis (Kurt). For excess returns we also present the CAPM beta and the coefficient estimate on the SAD onset variable, each estimated separately of the other. These coefficients are produced in a systems equation estimation using GMM and HAC std errors. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. For instruments for the CAPM regression, we use the market return, a constant, and one lag of each excess return. For instruments for the SAD regression, we use the onset variable, a constant, and one lag of each excess return.

Asset Class Fund Flows

Index	Mean	Std	Min	Max	Skew	Kurt
Risky Equity	0.561	1.00	-3.87	3.31	-0.538	2.12
Safe Equity	0.620	0.82	-2.55	4.25	0.861	2.99
Hybrid	0.795	1.36	-1.68	6.67	1.157	1.47
US Corporate Bond	0.780	1.26	-2.42	5.84	0.979	1.98
Global Bond	1.917	9.67	-7.05	138.57	11.301	154.18
General-Term Government	0.626	3.58	-3.92	25.94	3.613	15.87
Medium and Short-Term Government	0.624	3.09	-5.00	15.25	2.472	6.74
Munis	0.615	1.47	-3.89	6.02	1.479	3.48
Money Market	0.378	2.01	-5.02	8.50	0.797	2.48

Table 8 continues on next page

Table 8, Continued

Explanatory Variables

Index	Mean	Std	Min	Max	Skew	Kurt
Risky Equity Fund Specific:						
$R^{CapGains}$	2.357	8.24	-36.29	33.41	1.220	7.21
R^{Year}	1.173	1.34	-3.70	3.50	-1.079	1.12
Safe Equity Fund Specific:						
$R^{CapGains}$	2.407	8.17	-21.05	57.17	3.239	16.37
R^{Year}	1.195	1.18	-2.12	4.76	-0.324	0.86
Hybrid Fund Specific:						
$R^{CapGains}$	1.657	5.05	-6.90	25.82	2.879	8.52
R^{Year}	0.826	0.69	-0.98	2.22	-0.276	-0.49
US Corporate Bond Fund Specific:						
$R^{CapGains}$	1.555	4.49	-4.41	20.51	2.636	6.13
R^{Year}	0.775	0.54	-0.45	2.00	-0.164	-0.59
Global Bond Fund Specific:						
$R^{CapGains}$	2.575	9.89	-4.78	91.27	6.181	48.90
R^{Year}	1.269	1.65	-0.88	8.50	2.301	6.46
General-Term Government Fund Specific:						
$R^{CapGains}$	0.997	2.98	-7.36	13.46	2.435	6.50
R^{Year}	0.539	0.51	-0.79	2.51	0.746	2.02
Medium and Short-Term Government Fund Specific:						
$R^{CapGains}$	0.938	3.82	-4.28	32.91	5.338	37.48
R^{Year}	0.480	0.64	-0.55	3.10	1.391	3.14
Munis Fund Specific:						
$R^{CapGains}$	1.013	3.26	-4.34	19.92	3.266	12.28
R^{Year}	0.508	0.44	-0.58	2.04	0.528	1.24
Money Market Fund Specific:						
$R^{CapGains}$	1.008	3.00	-3.37	15.29	2.987	9.06
R^{Year}	0.508	0.37	-0.44	1.40	-0.470	0.33

Fund Excess Returns

Index	Mean	Std	Min	Max	Skew	Kurt	Beta	SAD
Risky Equity	0.768	4.58	-23.05	11.90	-0.996	3.28	1.026***	-1.532**
Safe Equity	0.806	4.12	-18.91	31.74	0.769	13.70	0.834***	-1.960***
Hybrid	0.434	2.51	-10.80	8.44	-0.767	2.27	0.509***	-.9224**
US Corporate Bond	0.384	1.34	-3.24	7.37	0.340	2.54	0.116***	-.3693*
Global Bond	0.933	4.74	-8.10	60.24	7.632	93.43	0.106***	0.5592
General-Term Government	0.089	1.47	-7.07	6.56	-0.064	3.25	0.005	0.8897***
Medium and Short-Term Government	0.033	1.34	-4.51	9.93	1.313	11.31	0.000	0.7380***
Munis	0.106	1.33	-6.34	4.19	-0.494	2.64	0.048***	0.6850***
Money Market	0.125	0.91	-2.75	5.98	1.317	7.74	-0.004	0.2552**

Table 9: Regression Results for Enlarged Set of Nine Asset Class Fund Flows

In this table we report coefficient estimates from jointly estimating the following regression for each of nine asset classes in a GMM framework:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \mu_{i,Savings}Savings_{i,t} + \epsilon_{i,t}. \end{aligned} \quad (1)$$

The data span January 1985 through December 2006. The monthly net flows are computed as sales, minus redemptions, plus exchanges in, minus exchanges out, all divided by the previous month's total net assets. The explanatory variables are defined in the text. In Panels A and B we present coefficient estimates with HAC robust t-tests in parentheses. At the bottom of Panels A and B we present the value of adjusted R^2 for each estimation, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test statistic for the presence of up to 12 lags of ARCH (both with 12 degrees of freedom). The test for ARCH is a standard LM test of order 12. See Engle (1982). To perform the test for autocorrelation, we augment our regression with 12 lags of the residuals, estimate MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors with OLS and test for the joint significance of these terms. Panel C contains joint test statistics. The first is a χ^2 statistic (with 10 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly zero across the fund asset classes, the second is a χ^2 statistic (with 9 degrees of freedom) testing the null that the onset/recovery coefficient estimates are jointly equal to each other across the fund asset classes, and the third is the Hansen (1982) χ^2 goodness-of-fit test of our model based on the optimized value of the objective function produced by GMM. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. The instruments used for the regression are the explanatory variables. 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 and Diagnostic Statistics

Parameter or Statistic	Risky Equity	Safe Equity	Hybrid	Corporate Bond - US	Corporate Bond - Global
μ	-0.434	-2.665***	-6.054***	-6.607***	-27.85***
	(-1.40)	(-14.8)	(-22.0)	(-25.6)	(-29.5)
$\mu_{\hat{OR}}$	-0.841***	-0.510***	-0.283*	-0.483***	0.926**
	(-7.15)	(-5.14)	(-1.66)	(-4.00)	(2.23)
μ_{Ads}	-0.059	0.245***	-0.157	-0.754***	-1.322***
	(-0.55)	(3.02)	(-1.14)	(-5.61)	(-3.00)
$\mu_{R^{Year}}$	0.167***	0.231***	0.715***	1.080***	0.854***
	(12.91)	(24.63)	(20.02)	(33.60)	(17.21)
$\mu_{CapGains}$	0.003**	-0.006***	-0.003	-0.011***	-0.040***
	(2.10)	(-5.23)	(-0.97)	(-4.14)	(-8.12)
μ_{Saving}	0.553***	1.809***	4.179***	4.777***	19.649***
	(3.21)	(16.64)	(23.95)	(31.34)	(31.63)
R^2	0.0931	0.2348	0.3036	0.4715	0.0824
AR(12)	111.83***	210.53***	337.13***	101.73***	12.23
ARCH(12)	29.74***	106.65***	68.73***	49.42***	63.41***

Table 9 continues on next page

Table 9, Continued

Panel B: Parameter Estimates and Diagnostic Statistics

Parameter or Statistic	Government General	Government Medium-, Short-Term	Munis	Money Market
μ	-17.61***	-7.908***	-6.397***	-0.046
	(-26.1)	(-14.3)	(-19.8)	(-0.09)
$\mu_{\hat{OR}}$	0.029	-0.261	-0.220	1.349***
	(0.11)	(-0.87)	(-1.45)	(6.55)
μ_{Ads}	-0.115	-0.820***	-0.346**	-0.557***
	(-0.40)	(-3.22)	(-2.41)	(-3.20)
$\mu_{R^{Year}}$	4.089***	3.391***	1.748***	0.786***
	(41.02)	(78.75)	(41.45)	(8.06)
$\mu_{CapGains}$	-0.028***	-0.016***	-0.008**	0.048***
	(-3.50)	(-2.61)	(-2.22)	(6.23)
$\mu_{Savings}$	10.527***	5.039***	4.226***	0.351
	(26.59)	(14.58)	(22.13)	(1.14)
R^2	0.5666	0.6739	0.5634	0.0649
AR(12)	172.91***	296.29***	102.94***	55.93***
ARCH(12)	49.92***	99.18***	73.95***	52.25***

Panel C: Joint Tests on Onset/Recovery Coefficient Estimates

Joint Test Across Fund Asset Classes	χ^2 [Degrees of Freedom]
$\hat{OR}$ jointly equal to zero across asset classes	128.8*** [9]
$\hat{OR}$ jointly equal across asset classes	110.8*** [8]
Test of Over-Identifying Restrictions	50.9 [144]

Table 10: Summary Statistics and Regression Results for Australia Equity Fund Flows

In this table we present summary statistics on monthly fund flows, explanatory variables, and returns for January 1992 through December 2006. Flows and equally-weighted monthly fund return data are from Morningstar. R^{Year} is the one-year moving average of fund percentage returns, to capture return chasing. We present the mean monthly values (Mean), standard deviation (Std), minimum (Min), maximum (Max), skewness (Skew) and kurtosis (Kurt).

Index	Mean	Std	Min	Max	Skew	Kurt
Australia Equity	0.457	0.59	-1.01	1.98	-0.143	-0.38
R^{Year}	1.111	0.93	-1.52	3.96	-0.221	0.53

Table 11: Regression Results for Australia Equity Fund Flows

In this table we report coefficient estimates from jointly estimating the following regression for each of nine fund asset classes in a GMM framework:

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}_{South}} \hat{OR}_{South_t} + \mu_{i,R^{Year}} R_{i,t}^{Year} + \rho_1 NetFlow_{i,t-1} \\ &+ \rho_3 NetFlow_{i,t-3} + \rho_6 NetFlow_{i,t-6} + \rho_{12} NetFlow_{i,t-12} + \epsilon_{i,t}. \end{aligned} \quad (4)$$

The data span January 1992 through December 2006. The monthly net flows are computed as sales, minus redemptions, plus exchanges in, minus exchanges out, all divided by the previous month's total net assets. The explanatory variables are defined in the text. 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 adjusted R^2 for each estimation, a Wald χ^2 test statistic for the presence of up to 12 lags of autocorrelation (AR), and a Wald χ^2 test statistic for the presence of up to 12 lags of ARCH (both with 12 degrees of freedom). The test for ARCH is a standard LM test of order 12. See Engle (1982). To perform the test for autocorrelation, we augment our regression with 12 lags of the residuals, estimate MacKinnon and White (1985) bootstrap heteroskedasticity-consistent standard errors with OLS and test for the joint significance of these terms. For this case we have no panel with joint tests. We have only one series so that the joint tests for SAD are redundant. The Hansen (1982) χ^2 goodness-of-fit joint test of our model is not valid as we have an exactly identified system. To calculate the standard errors we follow Newey and West (1994) and use the Bartlett kernel and an automatic bandwidth parameter (autocovariance lags) equal to the integer value of $4(T/100)^{2/9}$. The instruments used for the regression are the explanatory variables. One, two, and three asterisks denote significance at the 10 percent, 5 percent, and 1 percent level respectively, based on two-sided tests.

Parameter Estimates and Diagnostic Statistics

Parameter or Statistic	Australia Equity
μ	-0.142**
	(-2.07)
$\mu_{\hat{OR}_{South}}$	-0.365***
	(-2.85)
$\mu_{R^{Year}}$	0.138***
	(4.79)
ρ_1	0.133***
	(2.57)
ρ_2	0.260***
	(4.12)
ρ_3	0.257***
	(3.85)
ρ_6	0.125
	(1.06)
ρ_{12}	0.160***
	(2.68)
R^2	0.5764
AR(12)	14.5
ARCH(12)	12.7