Seasonal Asset Allocation: Evidence from Mutual Fund Flows

by

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Abstract

This paper documents a strong seasonality in flows between mutual funds that invest in different asset classes. While some of this seasonality is related to other influences, we find a strong correlation between investment flows (and exchanges) and the onset and recovery from seasonal affective disorder (SAD), consistent with the seasonally varying risk-aversion hypothesis of Kamstra, Kramer and Levi (2003). Specifically, our paper shows that substantial money moves from U.S. equity to U.S. government money market mutual funds in the fall, then back to equity funds in the spring, controlling for the influence of past performance, advertising, and capital gains overhang on fund flows and exchanges. While prior evidence regarding the influence of SAD relies on seasonal patterns in the returns on asset classes, our paper provides the first direct trade-related evidence. Further, we find a stronger seasonality in Canadian fund flows, consistent with its more northerly location and higher incidence of SAD, and a reverse seasonality in flows in Australian funds, consistent with the southern hemisphere seasons being offset by six months relative to the northern hemisphere.

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Seasonal Asset Allocation:
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Mutual fund flows are strongly predictable. For example, individuals invest heavily in funds with the highest prior-year returns, and disinvest weakly from funds with the lowest prior-year 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. For their part, mutual fund management companies have a strong incentive to understand the drivers of flows: 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 6.5 and 1.7 trillion dollars under management in all US-domiciled equity and bond mutual funds, respectively (Investment Company Institute, 2008).

Recent evidence indicates that flows represent the preferences or sentiment of small investors. For example, Ben-Rephael, Kandel, and Wohl (2011a) show that net exchanges of money from U.S. bond to U.S. equity funds exhibit a strong negative correlation with following-year returns in the market portfolio of equities; Indro (2004) also finds evidence consistent with equity fund flows being driven by investor sentiment.[1] Further, Ben-Rephael, Kandel, and Wohl (2011b) examine daily equity fund flows in Israel, and find a strong autocorrelation in mutual fund flows, as well as a strong correlation of flows with lagged market returns, which create temporary price-pressure effects.[2]

In this study, we document a heretofore unknown seasonality in mutual fund flows and net exchanges. We show that flows to (and exchanges between) fund categories (e.g., equity or money market), controlling for known influences, such as advertising expenditures, capital gains tax avoidance, and liquidity needs, are strongly dependent on the season, as well as the relative riskiness of the categories.

[1] Exchanges are movements of money between funds within a single fund family, and likely capture investor preferences rather than liquidity needs.

[2] Investors also react strongly to advertising by 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 on advertising annually to attract investment inflows (see Pozen, 2002).

Investors move money into (relatively) safe fund categories during the fall, and into riskier fund categories during the spring.[3,4] Further, we find strong evidence that this seasonality is correlated with risk-aversion driven by a medical condition known as seasonal affective disorder, or SAD, which is a seasonal form of depression.[5] It has been shown that depression is associated with increased risk aversion, both in general, and in the context of making financial decisions. 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).

While prior work has documented evidence consistent with seasonal risk-aversion of investors, our results provide new evidence on SAD-related investing behavior that is based directly on quantities of funds chosen by investors at a fixed price (the daily closing net asset value, NAV).[6] We believe that an examination of the trades of mutual fund shares represents a unique setting to study investor sentiment, since large quantities of shares may be purchased at that day's fixed NAV. Investor choice of quantities at a fixed price is more direct evidence than prior studies based on seasonality in asset class returns, since prices in most other markets adjust to the quantity demanded. These patterns of flows and net exchanges provide the

[3]A recent Toronto Star article (Marshman, 2010) reports on the most easily observable practitioner activity closely related to our findings, describing a new exchange-traded fund available to investors that engages in seasonal investing. Among its strategies are holding broad risky market indices (e.g., equities) for only the six "good" months of the year (which its managers identify as October 28 to May 5, applying the catchphrase "buy when it snows and sell when it goes"), and implementing seasonal trading strategies to individual sectors like oil and gas that see strong seasonal variation in demand for heating oil and gasoline.

[4]Discussions with a former academic who is now at a large global investment bank indicate that traders on the fixed income floor see low trading activity and high risk aversion during the last quarter of the year, which he describes as the "end-of-the-year effect." Then, risk taking and trading activity pick up markedly during the first quarter, which he interprets as people starting with a clean slate in terms of their risk budgets.

[5]Medical evidence firmly demonstrates that as the number of hours of daylight drops in the fall, some fraction of the population suffers from clinical depression associated with SAD. As Mersch (2001) and Thompson et al. (2004) note, estimates of the prevalence of SAD vary considerably, depending on the diagnostic criteria and sample selection methods employed by the researchers. Some studies find the incidence of SAD to be fairly high, such as Rosen et al.'s (1990) estimate of 10 percent, based on a sample in New Hampshire. Others find it is below 2 percent, such as Rosen et al.'s study of a sample in Florida. A recent study in Britain, using a relatively specific diagnostic method called Seasonal Health Questionnaire, found the prevalence of SAD was 5.6 percent (which is lower than the 10.7 percent detected on that sample using a less specific method known as the Seasonal Pattern Assessment Questionnaire). Up to an additional thirty percent of the population experiences Subsyndromal SAD, or winter blues, a milder form of the same condition (see Kasper et al. (1989), Rosen et al. (1990), and Schlager et al. (1995), among others). 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).

[6]In contrast, past work has focused on returns. For example, Kamstra, Kramer, and Levi (2003, 2011a) and Garrett, Kamstra, and Kramer (2005) document seasonal 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.

first direct evidence that some individual investors exhibit seasonal patterns in risk aversion that are associated with the amount of daylight present during different seasons.

Further, we study mutual fund flows and exchanges because they are largely the outcome of individual investor decisions. According to the Investment Company Institute (2008), 44 percent of all U.S. 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 sentiment of individual investors, and that a broad cross-section of individuals are involved in mutual fund markets. That is, if SAD has an influence on the investment decisions of some individuals, it is reasonable to expect the effects would be apparent in mutual fund flows and exchanges. Overall, flows and exchanges to mutual fund categories uniquely represent the decisions of buyers, or sellers, without the confounding influence of the counterparty to the trade (unlike stock trades, for instance).

Another contribution of our paper is that we employ a novel variable that captures seasonal risk-aversion 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. 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 a parametric structure on the link between daylight and risk aversion due to SAD effects).[7]

We use several datasets to study seasonality in flows, including U.S., Canadian, and Australian data. The U.S. data we employ are comprised of actual monthly flows to thirty mutual fund categories during 1985 to 2006, which we use to build 5 risk classes of funds: equity, hybrid, corporate fixed-income, government fixed-income, and money market. We also obtained data on net exchanges between

[7] We believe that this new, more direct measurement of SAD-related effects should be of interest to future research in this area.

these thirty fund categories, which are much less impacted by liquidity needs of investors (e.g., year-end bonuses or tax-season spikes in contributions) and, thus, add a cleaner view on the sentiment-driven trades of small investors. We study monthly flows (and exchanges) to these fund asset classes with a model that controls for previously documented influences on flows; specifically, we control for return-chasing, recent advertising, and capital-gains overhang.[8] We also add a control for personal savings, and explore models that explicitly control for autocorrelation in flows, as flows and exchanges are slowly mean-reverting.

With these U.S. flow and exchange data, we find empirical results that 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 between ten and fifteen billion dollars (circa 2006), and increases flows to money market funds by between two and seven billion dollars, on average, during the fall month of September, reversing in the spring month of March.[9] When we examine net exchanges, we find evidence of seasonality in investor sentiment consistent with our net flow data, though smaller in magnitude.

As an out-of-sample test of the SAD hypothesis, we examine Canadian mutual fund data for 10 fund classes, which we use to build 4 different risk classes of funds: equity, hybrid, fixed income, and global fixed income. This provides us with a similar but more northerly financial market compared to the U.S. If the SAD hypothesis is correct, we should see more exaggerated seasonal exchanges than we see in the U.S. Indeed, we find that net exchanges into (during the spring) and out of (during the fall) equity and hybrid fund classes show larger amplitudes in Canada than in the U.S., and we find remarkably larger fall exchanges into and spring exchanges out of Canadian safe asset fund classes (two to three times the magnitude we see in the U.S.), consistent with SAD impacting more northerly

[8]For instance, 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.

[9]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. As we show below, we find support for this view when we consider seasonalities in bank account inflows and outflows.

populations more markedly.

As a second out-of-sample test of the SAD hypothesis, we examine Australian flow data. For Australia, we were able to obtain data for only equity funds; however, if the SAD hypothesis is correct, these flows should show a seasonal cycle that is six months out of phase with northern hemisphere markets. This is exactly what we find; equity funds in Australia experience inflows during the the Australian spring and outflows in the fall.

The remainder of the paper is organized as follows. In Section I, 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 II, we define the measures we use to capture the impact of seasonal depression on investment decisions. In Section III, 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, controlling for these regularities. We introduce our U.S. flows data in Section IV, and we present our main findings in Section V. In Sections VI and VII we present our findings based on Canadian and Australian flows data, respectively. We describe additional robustness checks in Section VIII. Section IX concludes.

I 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 industry has emerged informing people how to deal with the disorder, and offering products that create "natural" light to help sufferers cope with symptoms.[10] Individuals who suffer from SAD can begin to experience the depressive effects of SAD or winter blues as early as July or August, but the bulk of people experience an initial onset during the fall. Individuals may begin recovering early in the new year, as the days lengthen, though most experience symptoms until spring. 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.[11]

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

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

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

averse) hold larger cash balances, roughly a third more than the average person, to meet unforeseen future expenditures. Further evidence 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) study approximately one thousand individuals in total, and find that sensation seeking scores are significantly positively correlated with the tendency to take financial risks.

Together, the evidence on lack of daylight leading to SAD, SAD leading to depression, and depression leading to greater 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 classes.

II 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 daylight, 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 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 a study of hundreds of SAD patients in Vancouver by Lam (1998b).[12]

First we construct a SAD "incidence" variable, which reflects the monthly pro-

[12] Young et al. (1997) similarly document the timing of SAD symptoms, but for onset only. We base our measure on the Lam (1998b) data because it includes the timing of both onset and recovery. Results are similar if we average the timing of onset from both the Lam and the Young et al. studies.

portion 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 0 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).[13] 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 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.[14]

$\hat{OR}_t$ 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 the first month of autumn, September. 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

[13]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.

[14]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 *net change* in incidence of symptoms.

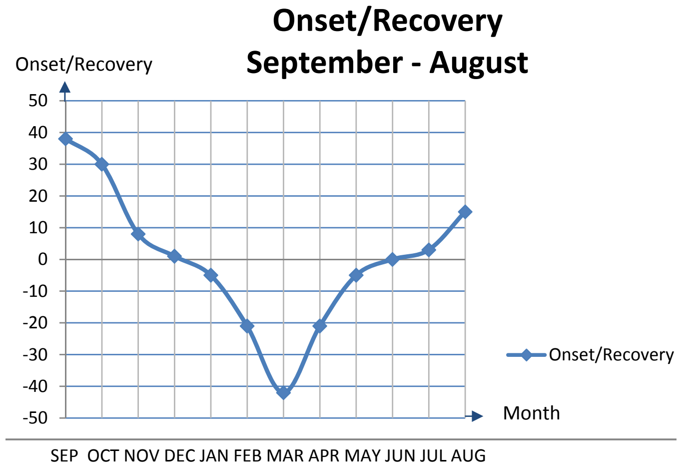

Figure 1: The onset/recovery variable reflects the change in the proportion of SAD-affected individuals actively suffering from SAD. The monthly series, calibrated to the 15th day of each month, is based on the clinical incidence of SAD symptoms among patients who suffer from the condition.

nor the length-of-day variable they employed is necessarily directly related to the onset and recovery from SAD.[15]

Some advantages of our onset/recovery variable are important to emphasize. First, our onset/recovery variable is based directly on the clinical incidence of SAD in individuals, unlike Kamstra et al.'s (2003) variables. Second, our onset/recovery variable spans the entire year, whereas Kamstra et al.'s (2003) 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 or later than winter. (For a more complete discussion of the merits of the onset/recovery variable relative to Kamstra et al.'s original specification, see Kamstra, Kramer, and Levi, 2011b.) In light of these points, we conduct our analysis using the onset/recovery variable.

III Seasonality in Mutual Fund Flows

In our analysis of mutual fund flows, the SAD hypothesis implies two questions. First, does the increased risk aversion that some investors experience with the diminished length of day in autumn lead to a shift from risky funds into low-risk

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

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.

A Controlling for Capital-Gains Distributions

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

Table I illustrates the seasonality in capital gains and dividend distributions to shareholders by presenting the percentage 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 paid during November, and 72% during December. Presumably, fund administrators wait until the end of their tax year (October 31) to compute their capital gains distributions, rather than attempting to distribute them more evenly through the year which could result in an unnecessary distribution of gains that are lost later in the year. To a much lesser extent, dividend distributions are also paid in greater quantity 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 of 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 not to 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, thus, we 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 one hundred 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 direct capital gain that will be realized by their sale of fund shares. For example, consider a shareholder who purchased his fund shares part way through the year, and only ten dollars of the year's one hundred dollars in total capital gains accrued since the time of his recent purchase. That shareholder may sell his or her shares prior to the dividend distribution instead of holding the stock and incurring the taxation associated with the one hundred dollar capital gain distribution. (He would be unable to recover taxes paid on the ninety dollars of excess capital gains until he ultimately sells the shares.)

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 fiscal 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.

B Other Empirical Regularities in Mutual Fund Flows

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 mutual funds 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 study the impact on fund flows of fund-specific characteristics, including fund age, investment style, and Morningstar rating.

IV Data

We obtained our U.S. datasets from the Investment Company Institute (ICI). These data consist of monthly flows to thirty mutual fund investment objective categories, covering the period of January 1, 1984 to January 31, 2010.[16] 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

[16] ICI provides data for thirty-three fund categories in total, however we omit three 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. Our results are qualitatively unchanged if, instead, we include these three omitted investment objective categories in our money market category.

out of money market funds, motivates us to end our sample in December 2006.[17] (Nonetheless, in untabulated robustness tests we find our results are qualitatively unchanged if we extend our sample period to include the financial crisis.) For each investment 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 mutual 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 II 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." (In Appendix A we show that our results are robust to a less coarse classification into nine asset classes.) Flows and assets are aggregated across all investment objective categories within an asset class to arrive at total asset class-level flows and assets.[18] We compute "active" net monthly flows to asset class i during month t, as a proportion of end-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 these are "passive flows."

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

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

Net exchanges are not subject to some confounding effects that may complicate the study of net flows, including income flows (i.e., liquidity considerations such as tax refund cash flows, year-end bonuses, and changes in savings/expenditure behavior.

In Table III, we report summary statistics for our data, including monthly asset

[17]For example, Wermers (2010) shows that flows to and from money funds during September 2008 were largely driven by fears of prime money funds "breaking the buck."

[18]We weight by TNA when computing variables such as asset class returns, and aggregate dollar flows to arrive at aggregate flows for an asset class.

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 excess returns (in Panel D). As previously mentioned, fund flows are reported as a proportion of the fund's prior end-of-month total net assets.

From Panel A, we can see that the mean monthly equity class net flow is 0.59 percent of equity class TNA. The hybrid class has a mean monthly net 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 net 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 exchanges which should, and do, net across asset classes to within a few basis points of zero (after weighting by the respective asset class prior-month asset values). The volatility of net exchanges is smaller than net flows, consistent with their lower average level, and the skewness is negative compared to the positive skewness of net flows (with the exception of the money market funds, which display remarkably positively skewed exchanges relative to flows). Also, net exchanges are strongly fat-tailed, as evidenced by kurtosis 8 to 12 times that of net flows.

In Panel C we first present statistics for advertising and savings. Our advertising variable is monthly print advertisement expenditures by mutual fund families (detrended by dividing by the previous year's total advertisement expenditure to account for time-series trend-line growth).[19] We include a measure of savings to control for the possibility that investor liquidity has an influence on flows. Our savings variable is calculated by subtracting Real Personal Consumption Expen-

[19] 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.

ditures (BEA series ID PCEC96) from Real Disposable Personal Income (BEA series ID DSPIC96), divided by DSPIC96, 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 Bureau of Economic Analysis (BEA) savings rate (which is reported in the press) shows an average monthly savings rate of 0.4% over this period.[20] Panel C also reports summary statistics for the one-year moving average return (R^{Year}, our return-chasing proxy) and the cumulated return ($R^{CapGains}$, our proxy for the influence of capital gains overhang in November and December) of each asset class.[21] R^{Year} is the return over the prior 12 months, and $R^{CapGains}_{i,t}$ equals the cumulated return to holding the fund from the previous year's November 1 (the start of the tax year for mutual funds) to the current year's October 31. $R^{CapGains}_{i,t}$ is set to zero in all months other than November and December. As a result, $R^{CapGains}_{i,t}$ is about twice the magnitude of R^{Year} and considerably more volatile.

Panel D contains summary statistics for the monthly excess asset class returns.[22] The return for month t and asset class i is calculated as $R_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} - NetFlow_t}{TNA_{t-1}}$.[23] All these return data reveal familiar patterns, with equity returns being the largest and the most volatile, declining virtually monotonically across categories, 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 beta, suggesting a declining exposure to systematic risk across this ordering of fund asset classes. We also present the coefficient on the onset/recovery variable from a regression of excess returns on onset/recovery. This tells us how

[20]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.

[21]We perform robustness checks on our return-chasing proxy with the use of a one-quarter moving average return, and we also include several alternative measures to capture capital gains overhang. See Section VIII for a complete description.

[22]Our excess returns are calculated conventionally, using the 30-day T-bill rate as the risk-free proxy return, sourced from CRSP.

[23]Note that this expression assumes that all distributions are reinvested. Our discussions with staff at the Investment Company Institute indicate that over 80% of investors reinvest capital gains and dividend distributions.

strongly the fund asset returns themselves correlate with SAD onset/recovery.[24] The pattern of onset/recovery coefficients from these excess return regressions are consistent with the other evidence of relative risk across asset classes; the equity class has the largest negative coefficient, and the two safest classes, government fixed income and money market, both show strong positive coefficient estimates.

Finally, in Panels E and F we present net flow and net exchange correlations across fund categories. For net flows (Panel E), we note that correlations between riskier categories, such as equity and corporate fixed income, are generally much higher than correlations between high- and low-risk categories, such as equity and money market. For net exchanges, it is even clearer that investors chiefly move money between the risky categories and the money market category. Overall, the correlations appear consistent with the notion that investors move money between categories due to time-varying risk aversion.

In Figure 2, we consider unconditional patterns in asset class fund flows. More formal analysis follows. The monthly average flows for the equity and money market asset classes are plotted in Panels A and B of Figure 2, respectively, in a thick solid line. The plot starts with the first month of autumn. The unconditional seasonal patterns in equity and money market 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 (higher)-than-average net equity (money market) 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 and less interested in holding safe assets. Accordingly, we see equity (money market) net flows are higher (lower) than

[24] The CAPM beta and the coefficient estimate on the SAD onset/recovery variable are 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. We use the CRSP value-weighted total market return, including dividends for our market return. The instruments used for the SAD regression are the onset/recovery variable, a constant, and one lag of each excess return.

Average Monthly U.S. Net Flows and Predicted SAD Flows: Equity and Money Market

Panel A
Equity

Panel B
Money Market

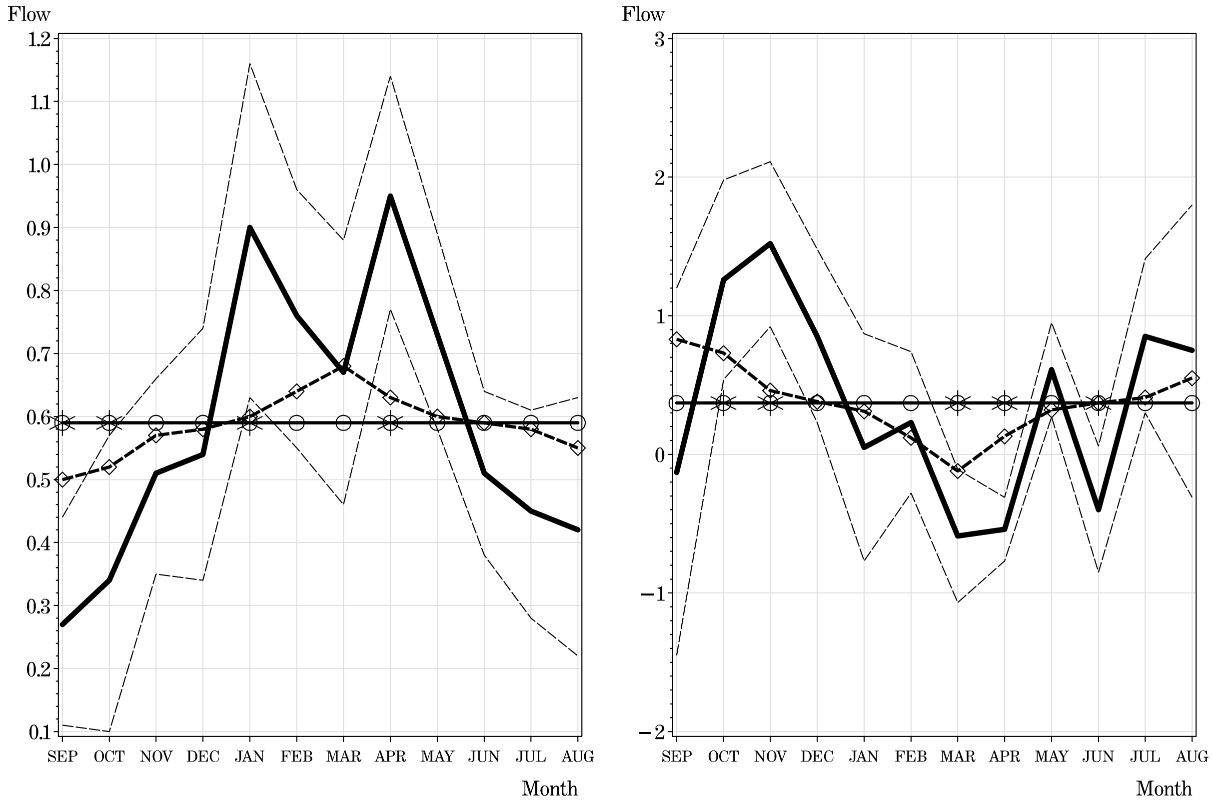

Figure 2: Panel A contains monthly average **equity** asset class fund net flows as a proportion of prior-month equity class TNA, indicated with a thick solid line, and average fitted values implied by the onset/recovery coefficient from estimating Equation (1), indicated with a dashed line with diamonds. Panel B contains monthly average **money market** asset class fund net flows as a proportion of prior-month money market TNA, indicated with a thick solid line, and 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 thin 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 to December 2006.

average during that period. Overall, the flows in the summer/fall and winter/spring are consistent with SAD-affected investors shifting their portfolios between risky and safe funds depending on their seasonally varying risk aversion.

The thin dotted lines surrounding the thick line are the 90% confidence intervals around the average monthly flows.[25] Consistent with the intuition from the

[25]There are several approaches one could adopt to calculate the confidence interval around the mean monthly net 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

seasonal pattern of flows, we see several instances of statistically significant (unconditional) deviations of the equity (money market) fund flows from annual mean flows, lower (higher) in the summer/fall, higher (lower) 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 implied by SAD, controlling for other effects like capital gains and autocorrelation in flows, seems to track the unconditional seasonal pattern in flows fairly well.

Unreported plots for the hybrid class, corporate fixed income class, and government fixed income class show seasonal flow patterns that lie between the extremes of equity and money market fund flows. This is perhaps not surprising, given that these other classes are intermediate in their exposure to risk relative to equity and money market asset classes, as measured by fund excess return beta and SAD coefficient estimates shown in Table III and consistent with practitioner classifications of the risk involved in holding these various fund classes.

V Results

In this section we first consider U.S. net flows. These include flows between fund families. Next we consider net exchanges, i.e., *within-family* movements of money, such as a movement from Fidelity equity to Fidelity money market funds. Net exchanges control better for liquidity-related reasons to move money into or out of fund categories. For example, net exchanges would not be impacted by someone buying equity funds with year-end bonus money or selling funds for liquidity reasons. After discussing estimation results for both sets of flow measures, we discuss the economic magnitude of the findings.

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 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 monthly dummy variables.

A The Net Flows Regression Model

There is considerable autocorrelation in fund flows, so we estimate a model that incorporates lags of the dependent variable to directly control for autocorrelation. Specifically, we include one-month, three-month, six-month, and twelve-month lags of the dependent variable as regressors. (In Appendix B we show that our results are robust to estimating a model that excludes lags of the dependent variable.) The complete model we estimate is as follows:

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

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 1 (the start of the tax year for mutual funds) to the current year's October 31. $R^{CapGains}_{i,t}$ is set to zero in all months other than November and December. $Savings_{i,t}$ is personal savings, lagged one period. Personal savings is included as a control variable for investor liquidity needs, which might also affect fund flows in a seasonal way.

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.[26] Results from estimating this set of equations are shown in Ta-

[26] Our use of HAC standard errors is due to the fact that autocorrelation and heteroskedasticity are a prominent feature of all classes of fund flows. See Warther (1995), Remolona, Kleiman, and Gruenstein (1997), and Karceski (2002), among others.

ble IV. In Panel A we present coefficient estimates and two-sided t-tests. The bottom of Panel A contains the adjusted R^2 for each asset class model and χ^2 statistics for testing for the presence of up to 12 lags of autocorrelation or ARCH. See Engle (1982).

Consider, first, the coefficient estimates on the onset/recovery variable. The riskiest category, equities, has a significantly negative coefficient estimate. Recall that the onset/recovery variable itself is positive in the summer/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 summer/fall and above-average in the winter/spring, as displayed in the unconditional plot in Figure 2. The onset/recovery coefficient estimate is positive and statistically significant for the safest asset class, the money market category, implying money market fund flows are expected to be above average in the summer/fall and below average in the winter/spring, again as we see unconditionally. While we focus attention on the safest and riskiest categories of funds, we note that the categories with risk that lies between the equity and money market extremes (hybrid, corporate, and government fixed income) all have negative coefficients on $\hat{OR}_t$. Onset/recovery for the government fixed income fund flows show only weak statistical significance relative to the other fund classes.

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 statistic 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, supporting the position that the safe and risky funds do indeed exhibit different seasonal cycles in flows related to the

To calculate 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 $4(T/100)^{2/9}$ We also explored the use of seemingly unrelated panel regression estimation with MacKinnon and White (1985) heteroskedasticity-robust standard errors and sufficient lags to control for autocorrelation. This approach yields very similar results to GMM for both significance and magnitude of effects. The instruments used for the regression includes the full set of explanatory variables. Specifically, for each equation we include $\hat{OR}_t$, Ads_t, $R_{i,t}^{Year}$, $R_{i,t}^{CapGains}$, $Savings_t$ and the lags of the dependent variable used in the regression.

onset/recovery variable. We also provide a χ^2 goodness-of-fit test of our model.[27] The goodness-of-fit test indicates that the over-identifying moment restrictions we use to estimate the model are not rejected.

Consider now other coefficient estimates shown in Table IV. The advertising expenditure coefficient estimate is positive for the equity and hybrid classes, and is strongly significantly negative for the remaining classes. 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 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 and the equity fund class (for which it has vary small magnitude), which is broadly consistent with investors having a tendency to avoid purchasing funds that have substantial realized gains to distribute.[28] The savings variable is strongly significantly positive for all classes of funds except the money market class, consistent with the notion that liquidity has an important impact on flows for most classes of funds.

B Fit of the Net Flows Model

Recall that the dotted lines with diamonds that appear in Figure 2 represent *fitted values implied by the SAD onset/recovery coefficient* from estimating Equation (1). It is also interesting to explore whether our *full model* can account for seasonalities only partially captured by SAD. In Figure 3 we plot the equity and money market monthly flows together with the average fitted values implied from the full model, indicated by a dashed line with diamonds.

The full model, accounting for conditional effects and autocorrelation in flows, fits the unconditional seasonality in fund flows well. Indeed, analysis of the residuals

[27] Hansen (1982) details conditions sufficient for consistency and asymptotic 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.

[28] Money market funds do not normally distribute significant capital gains, so we suspect the positive coefficient on $\mu^{CapGains}$ for the money market category arises due year-end return-chasing in money market funds. We believe the positive coefficient on $\mu^{CapGains}$ for the equity class arises due to investors' sale of poorly performing equity funds at year-end in order to realize capital losses.

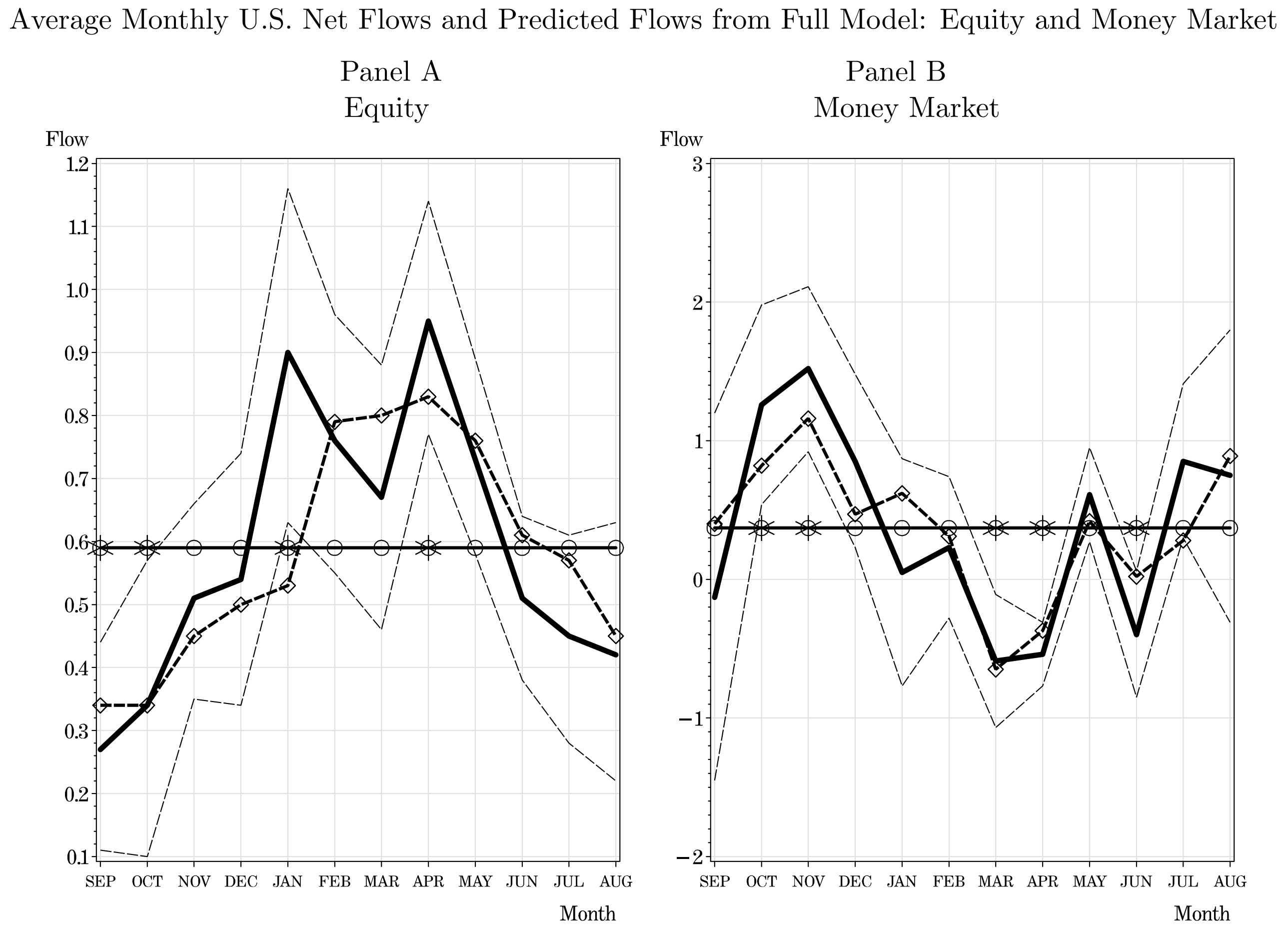

Figure 3: Panel A contains monthly average **equity** asset class fund net flows as a proportion of prior-month equity class TNA, indicated with a thick solid line, and average fitted values implied from estimating Equation (1), indicated with a dashed line with diamonds. Panel B contains monthly average **money market** asset class fund net flows as a proportion of prior-month money market TNA, indicated with a thick solid line, and average fitted values implied 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 thin 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.

from this model shows no remaining seasonality in equity or money market flows. The *time-series* fit of the models is shown in Figure 4. Note that we plot all available data, including data we do not use to estimate the models, 2007 and beyond. Panel A of Figure 4 corresponds to the equity fund flows and Panel B of Figure 4 corresponds to money market fund flows. 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 are likely less precise prior to 1996.[29] The flows

[29]The ICI told us that they reorganized categories in 1996 and that the precision of their flows estimates also improved afterwards.

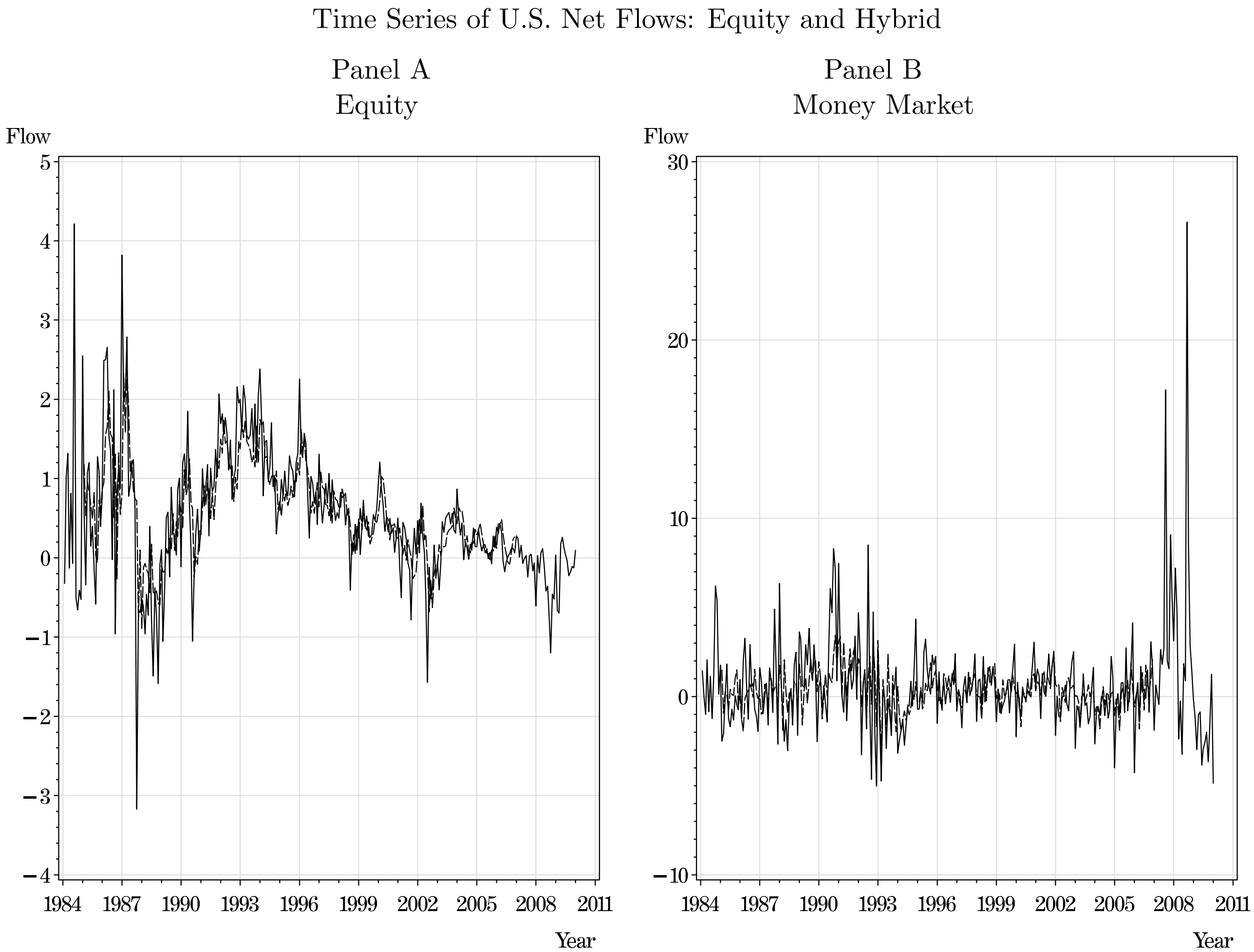

Figure 4: Panel A contains the time series of monthly **equity** fund net flows as a proportion of equity class TNA, indicated with a solid line, and the monthly fitted values from estimating Equation (1), indicated with a dashed line. Panel B contains the time series of monthly **money market** fund net flows as a proportion of money market 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 2009. The model is estimated over the period 1985-2006, hence the fitted series ends earlier than the realized series in the plot.

corresponding to hybrid, corporate bond and government bond asset classes are very similar to the equity and money market asset classes and are not presented. Generally, these models are able to match the data well, in particular the seasonal periodicity (a feature most obvious in the money market asset class), in spite of the huge flow variation over 2007-2008.

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 qualitatively unchanged.

C Investor Sentiment and Mutual Fund Flows: Net Exchanges

Ben-Rephael, Kandel, and Wohl (2011a) 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 (2011a) suggest that net exchanges reflect the asset allocation decisions of fund investors, in contrast to sales net of redemptions which incorporate long term savings and withdrawals as well as short-term liquidity needs. If SAD indeed impacts investor asset allocation decisions then a clear implication of Ben-Rephael, Kandel, and Wohl's (2011a) claim is that this impact should be evident in net exchanges.

The regression model we consider for net exchanges is:

$$\begin{aligned} NetExchange_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \rho_{i,1}NetExchange_{i,t-1} + \rho_{i,3}NetExchange_{i,t-3} \\ &+ \rho_{i,6}NetExchange_{i,t-6} + \rho_{i,12}NetExchange_{i,t-12} + \epsilon_{i,t}, \end{aligned} \quad (2)$$

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 to 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 (1987) HAC standard errors. Table V contains estimation results. 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 significantly negative for the riskiest asset class, equities, and significantly positive for the safest class, money market. Just as we saw in the cases discussed above, the money market class displays the largest percentage effect from SAD. For the three categories between the safest and riskiest extremes, we see a mix of positive and negative coefficient estimates, only weakly positive for the hybrid class. In this table, the magnitudes of the coefficient estimates on the intermediate risk categories lie between the values for the equity and money market categories.

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 to estimate the model are not rejected. We get very similar results if we exclude the lagged net exchanges, though the significance of the onset/recovery variable is reduced.

D 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 IV (based on net flows), the $\hat{OR}$ coefficient estimate is 1.2 for the money market class. To calculate economic impact, we multiply 1.2 by the value of the onset/recovery variable for a given month. In September, onset/recovery equals 38 percent (as reported in Section II). Thus, the average economic impact of SAD on money market fund flows in the month of September is roughly 45 basis points of the total net assets of the taxable government money market class at the end of the prior August.

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 45 basis points of TNA we calculated above yields a

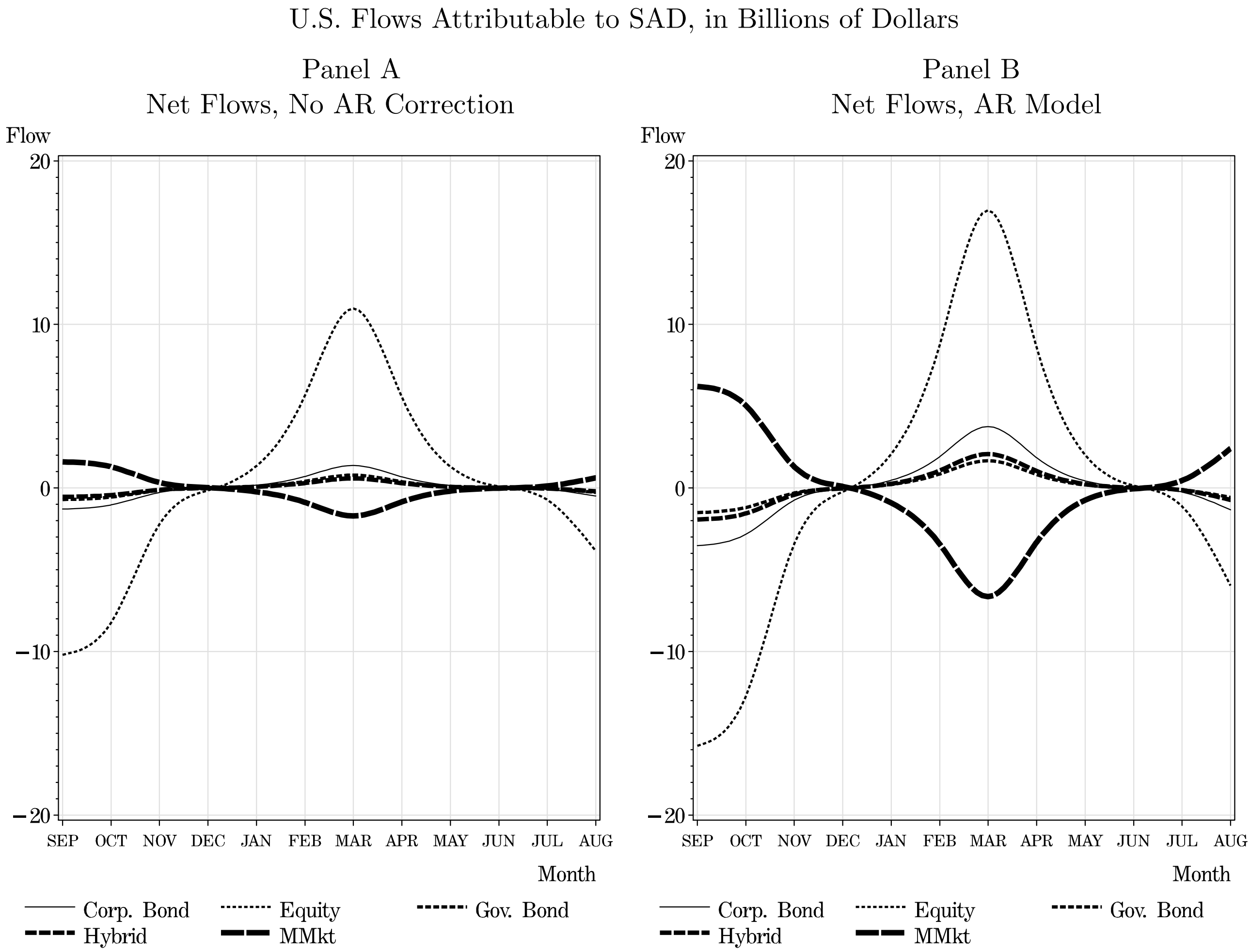

Figure 5: This figure contains the monthly flows due to SAD, in billions of dollars, by fund asset-class, for 2006. The legend indicates which lines represent which classes, provided by the Investment Company Institute. Panel A presents total net flows predicted from Equation (5), a model with no autoregressive terms (detailed in Appendix B), Panel B presents total net flows predicted from Equation (1), the model with autoregressive terms.

SAD-associated economic impact of over 1.5 billion dollars flowing into the money market asset class in September 2004. In the spring, the economic impact was such that about 1.7 billion dollars flowed out of money market funds in March 2005. These are immediate impacts, not accounting for the autocorrelation in the flows, which blurs the impact. Accounting for autocorrelation leads to a total impact closer to 5 to 6 billion dollars.[30]

In Figure 5 we summarize the economic impact for all five asset classes, for 2006, from a model for net flows without autoregressive terms (detailed in Appendix B) and from our model for net flows that incorporates autoregressive terms. Each line

[30]To get the long run impact in the setting of a model with autoregressive terms we inflate the immediate impact by dividing by one minus the sum of the autoregressive coefficients. In the case of money market flows, we can see from Table IV that this amounts to multiplying by roughly 4. We plot the long run impact in Figure 5.

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. Our estimated models for the impact of SAD onset and recovery suggest that SAD reduces net flows to equity funds between ten and fifteen billion dollars (circa 2006), and increases flows to money market funds by between two and seven billion dollars, on average, during the fall month of September, reversing in the spring month of March. Net exchanges are approximately twenty-five percent as large as net flows. 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, even approximately, to zero across our categories. When aggregated across all fund categories, the net flows attributable to SAD indicate that outflows in the fall and inflows in the winter are at maximum about five billion dollars per month. This raises the question, is there some other counterbalancing category of savings to/from which funds flow? The largest savings category is, perhaps, bank accounts, including checking, savings, and money market accounts (separate and distinct from money market mutual funds).

D.1 Unbalanced Flows?

We considered deposit data (adjusted for inflation but unadjusted for seasonality) provided by the Board of Governors of the Federal Reserve System.[31] 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 monthly winter outflows average to just over four billion dollars, a good match to the low estimate for the unaccounted-for winter fund flows, but the fall bank account inflows are large, at roughly nineteen billion dollars per month. Some of these flows are likely an artifact of saving in advance of holiday spending, and

[31] We obtained seasonally unadjusted 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 U.S. Department of Labor: Bureau of Labor Statistics).

saving does peak late in the quarter. If we leave out the December buildup in deposits, we have an average monthly increase of approximately ten billion dollars, a good match to the high end of the unaccounted-for fall fund flows.

VI Canadian Flows

In this section, we explore the seasonality of mutual fund flows in Canada, a similar but more northerly financial market relative to the U.S. Since Canada's population resides at latitudes north of the U.S., if the SAD hypothesis is correct we should see more exaggerated seasonality in flows than we see in the U.S.[32] The Investment Funds Institute of Canada (IFIC) provided us with Canadian fund flow data that is similar to the previously described ICI data for the U.S. The IFIC data were provided based on 10 categories of funds which we translate into four broad categories: equity, hybrid, fixed income, and global fixed income. In Appendix C we provide details on the construction of the four categories of Canadian funds.

Table VI contains summary statistics on the Canadian data.[33] The range of the data extends from December 1990 through December 2006. (The need for lagged values restricts our estimation period to start in January 1992.) Net exchanges are reported as a proportion of the fund's prior end-of-month total net assets. Panel A reports summary statistics on net exchanges across asset classes, the means of which net to close to zero (after weighting by the respective asset class prior-month asset values). The volatility of net exchanges is similar to that for U.S. fund exchanges, the skewness is negative except for equities, and the net exchanges are strongly fat-tailed, again similar to U.S. net exchanges. Panel B contains summary statistics for the mean monthly return over the past year (R^{Year}, our return-chasing proxy) and the capital gains proxy ($R^{CapGains}$, the cumulated return to holding the fund from the previous year's January 1 – the start of the tax year in Canada – until month $t-1$).[34]

[32]The U.S. population centroid (mean center) is approximately 37 degrees north (U.S. Census Bureau, based on the 2000 census), whereas the Canadian population centroid is approximately 48 degrees north. See Kumler and Goodchild (1992).

[33]In Appendix C we additionally provide summary statistics on Canadian net flows and savings data.

[34]Recall that for the U.S., the capital gains proxy is zero for all months other than November and December, consistent with the October 31 tax year-end for mutual funds in the U.S. Because the start of the Canadian tax year is January 1,

Panel C contains summary statistics for the monthly excess asset class returns (in excess of the 30-day U.S. Treasury rate, although results are not sensitive to the risk-free rate employed). The month t return for asset class i is calculated as $R_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} - NetFlow_t}{TNA_{t-1}}$, which assumes that all distributions are reinvested in the funds. The data reveal familiar patterns, with equity and hybrid excess returns being the largest and most volatile, although global fixed income has been quite volatile over our sample period. The excess returns show a monotonically declining CAPM beta, suggesting a declining exposure to systematic risk across this ordering of fund asset classes. We also present $\hat{OR}$ coefficient estimates from a regression of excess returns on SAD onset/recovery. These estimates are consistent with the SAD risk aversion hypothesis: large and negative for equity and hybrid classes, and large and positive for fixed income.

Panel D contains correlations between monthly net exchanges for the categories. Note that the strongest correlation is -0.81, which is the correlation between the equity and fixed income categories. As with the U.S. data, investors tend to commonly fund equity fund investments by redeeming safer fixed income investments, and vice-versa. (Correlations based on net flows are provided in Appendix C.)

In Figure 6, we consider unconditional patterns in net exchanges for two IFIC asset classes, equity funds (Panel A) and fixed income funds (Panel B), represented by thick solid lines. The unconditional seasonal patterns in the Canadian net exchanges are very similar to that seen in the U.S.: net exchanges are below (above) average for equity (fixed income) funds during the summer/early fall, and above (below) average during the winter/early spring. This unconditional evidence is consistent with SAD impacting exchanges, where SAD-affected investors shift their portfolios between risky and safe funds depending on their seasonally varying risk aversion. In each panel, the thin dotted lines surrounding the thick solid line

there is no analogous two month overhang period in Canada. Nonetheless, for Canada we include a year-round capital gains variable designed to capture capital gains overhang that may occur in any month of the year. This is motivated by the fact that an investor who purchases a fund may face capital gains taxes on gains that were realized earlier in the tax year, prior to his purchase. Thus for Canada we define $R^{CapGains}$ as the cumulated return from start of tax year until month $t-1$. This variable takes on non-zero values for all months of the year except January. ($R^{CapGains}$ is zero in January by construction.) Our primary findings for Canada are robust to excluding this capital gains variable from our model. Further, our primary findings for the U.S. are robust to many different ways of controlling for capital gains overhang, as described in our robustness checks reported in Section VIII.

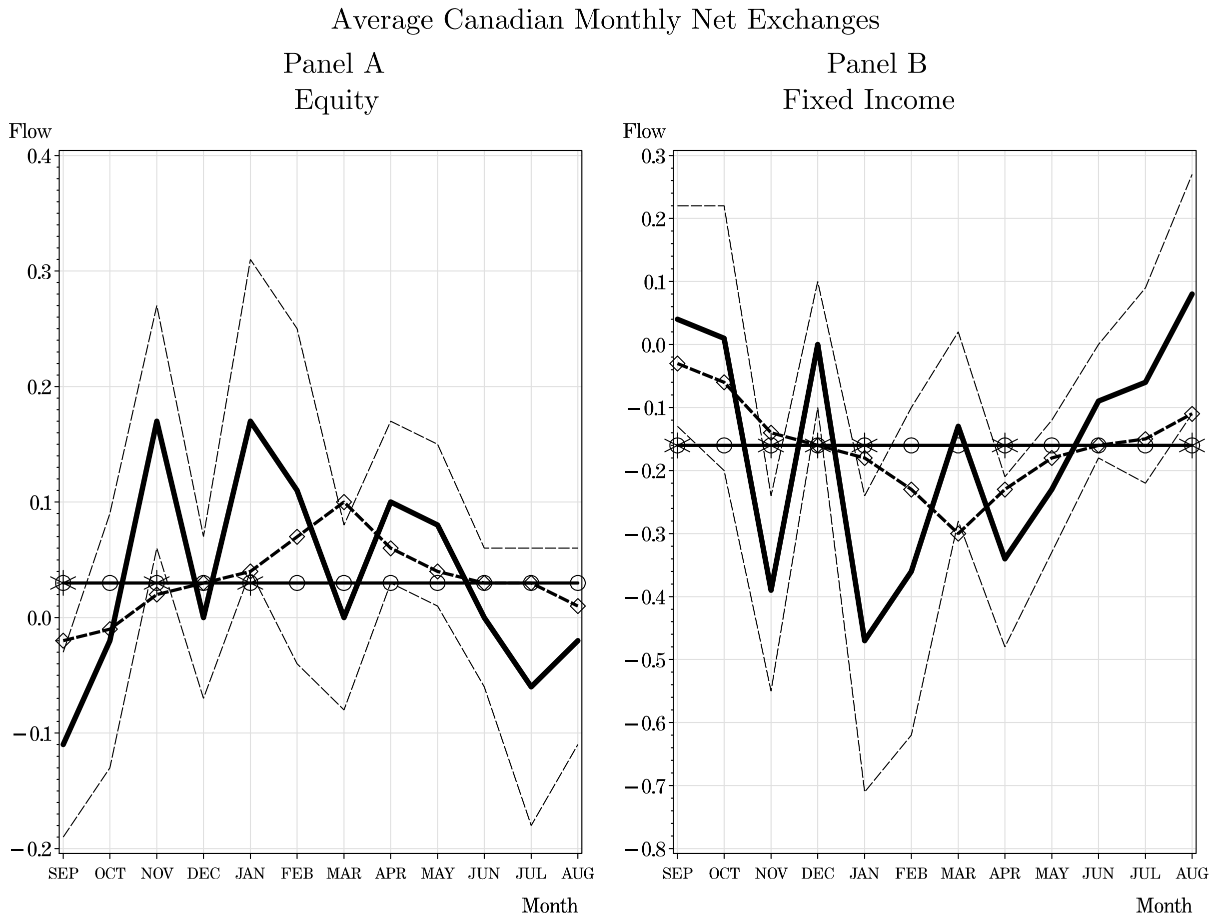

Figure 6: Panel A plots monthly average **equity** asset class fund total net exchanges, Panel B monthly average **fixed income** asset class fund total net exchanges (both as a proportion of prior-month fund TNA), indicated with a thick solid line, and average fitted values implied by the onset/recovery coefficient 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 thin dashed lines) and the average exchanges 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 Funds Institute of Canada, span January 1992 through December 2006.

are the 90% confidence intervals around the average monthly exchanges.[35] We see several instances of statistically significant (unconditional) deviations of the equity fund exchanges from annual mean exchanges, lower in the summer/fall, higher in the winter/spring. The dashed line marked with diamonds represents the average monthly fitted values predicted from the impact of the onset/recovery variable in a regression model that controls for various other conditional effects (Equation (3), which we introduce below). Unconditional plots and summary statistics are consistent with SAD influencing exchanges seasonally, but these are no substitute for

[35]These confidence intervals are produced similarly to our approach for U.S. flows and exchanges. We exploit the information in the cross-sectional variability across the fund asset classes by using a system of equations with the data and estimating a fixed-effects model with twelve dummy variables (one for each month). Again, 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 monthly dummy variables.

formal conditional analysis. We turn now to regression analysis.

A Regression Model

The regression model we consider is:

$$\begin{aligned} NetExchange_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \rho_{i,1}NetExchange_{i,t-1} + \rho_{i,3}NetExchange_{i,t-3} \\ &+ \rho_{i,6}NetExchange_{i,t-6} + \rho_{i,12}NetExchange_{i,t-12} + \epsilon_{i,t}, \quad (3) \end{aligned}$$

where i references the mutual fund asset class. 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. $\hat{OR}_t$ is the SAD onset/recovery variable. 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 exchanges. $R^{CapGains}_{i,t}$ is included to control for the influence of capital gains overhang on exchanges. Unlike the U.S., mutual funds in Canada did not face the U.S. Tax Reform Act of 1986, and tax reporting on capital gains follows the tax year, January through December. Hence $R^{CapGains}_{i,t}$ equals the cumulated return to holding the fund from the start of the tax year until month $t-1$ (this variable equals zero for January). Unfortunately, we were not able to obtain Canadian fund family advertising data.

We estimate Equation (3) as a system of equations using Hansen's (1982) GMM and Newey and West (1987) HAC standard errors.[36] Table VII contains estimation results. In Panel A we present coefficient estimates and two-sided t-tests. The bottom of Panel A contains the adjusted R^2 for each asset class model and χ^2 statistics for testing for the presence of up to 12 lags of autocorrelation or ARCH.

Consider, first, the coefficient estimates on the onset/recovery variable. The equity and hybrid asset classes both have negative and statistically significant coefficients on $\hat{OR}_t$. Recall that the onset/recovery variable itself is positive in the

[36] To calculate 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 includes the full set of explanatory variables. Specifically, for each equation we include $\hat{OR}_t$, lags 1, 3, 6, and 12 of the dependent variable, $R^{Year}_{i,t}$, and $R^{CapGains}_{i,t}$.

summer/fall and negative in the winter/spring (see Figure 1). Thus, the implication is that equity fund exchanges are expected to be below-average in the summer/fall and above-average in the winter/spring, as displayed in the unconditional plot in Figure 6. The onset/recovery variable is positive and statistically significant for both of the fixed income asset classes, implying fixed income fund exchanges are expected to be above average in the summer/fall and below average in the winter/spring, again as we see unconditionally. It is interesting to compare the magnitude of the coefficient estimates on the onset/recovery variable for Canadian fund exchanges and U.S. fund exchanges. One way to identify the SAD effect, distinct from other seasonal influences, is to consider an implication of the SAD hypothesis, that exchanges should be more pronounced the further the market is away from the equator, as the prevalence of SAD generally increases with distance from the equator. Indeed, the percentage net exchange magnitudes for the Canadian risky fund asset classes are, on average, slightly larger than for the comparable U.S. funds, and are remarkably larger for the safe fund asset classes, two to three times the magnitude of U.S. net exchanges. Of course the dollar magnitudes of both these exchanges are much larger for U.S. funds due to the size of the U.S. market. The remaining coefficient estimates are similar to what we have seen earlier; there is strong evidence of autocorrelation, return chasing, and some impact consistent with the avoidance of funds that have experienced recent capital gains.

In Panel B, we present statistics testing the joint significance of the onset/recovery coefficient estimates and a test of model fit. These tests, as we have seen for the case of U.S. fund flows and exchanges, provide strong evidence consistent with a SAD seasonal in fund exchanges, and the goodness-of-fit test indicates that the over-identifying moment restrictions we use to estimate the model are not rejected.

The time-series fit of the models is shown in Figure 7, Panels A and B, for the equity and money market asset fund cases respectively. We can clearly see the noisiness of the series from these plots as well as the impact of some notable macro events like the 1998 currency crises and the year-2000 tech boom.

In Figure 8, we summarize the average economic impact from net flows and

Time Series of Canadian Net Exchanges

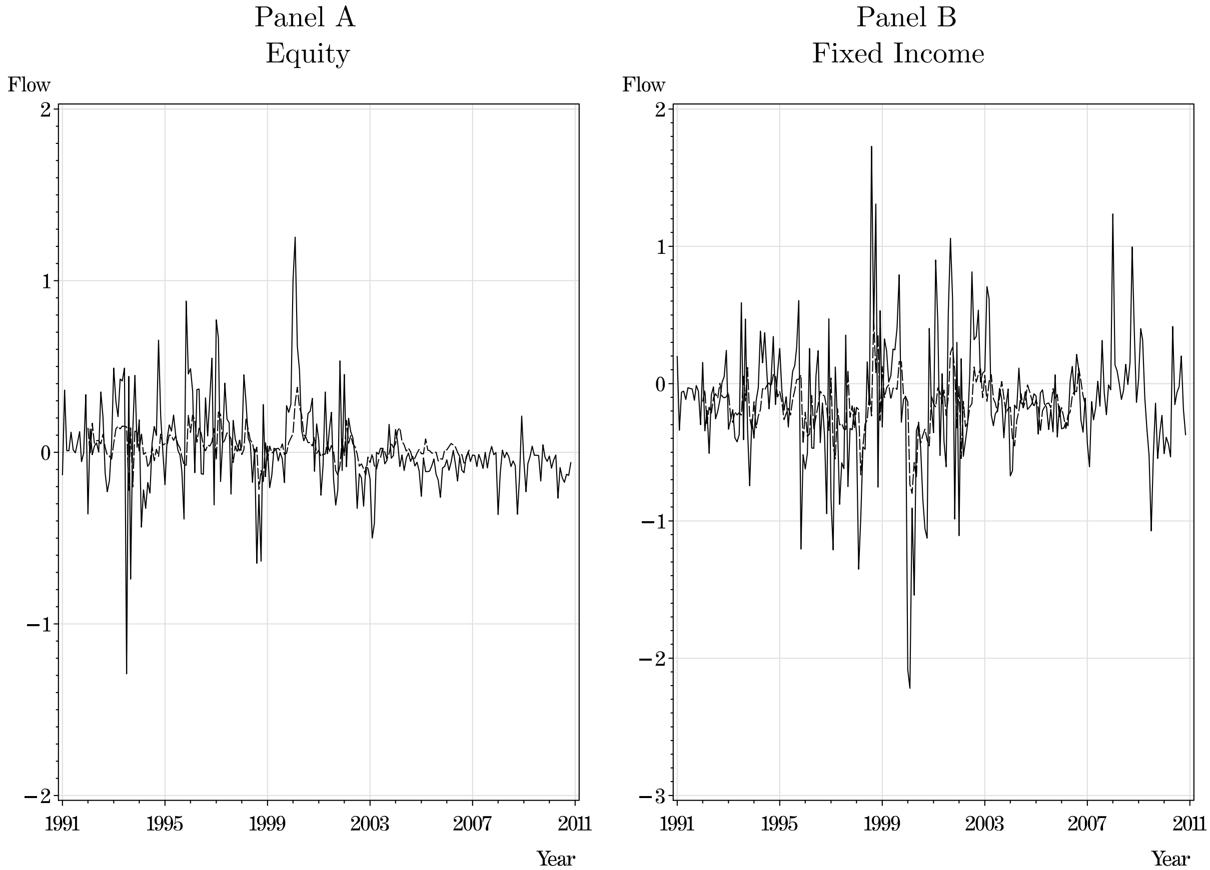

Figure 7: Panel A contains the time series of monthly **equity** fund net exchanges and Panel B the time series of monthly **fixed income** fund net exchanges (both as a proportion of fund TNA), indicated with a solid line, and the monthly fitted values from estimating Equation (3),indicated with a dashed line. The data, provided by the Investment Funds Institute of Canada, span January 1991 through December 2010. The model is estimated over the period January 1992 through December 2006, hence the fitted series starts later and ends earlier than the realized series in the plot.

from net exchanges associated with SAD for Canadian funds, for 2006.[37] The model used to produce the economic impact of SAD on net flows is the regression model estimated in Appendix C. (This is a model with Canadian net flows as the dependent variable with lags of the dependent variable and other Canadian data included as regressors, analogous to Equation (1) estimated for the U.S.) Each line represents the average monthly economic magnitude of the SAD effect for a given asset class. The thin solid line that varies most corresponds to the equity class and the thickest dashed line that moves in an opposing fashion is the global bond category. The annual oscillation in Canadian equity fund flows due to SAD, as shown in Panel A, is in the order of plus-or-minus 1.5 billion dollars.[38] (This

[37]To estimate the long run impact in the setting of a model with autoregressive terms, we inflate the immediate impact by dividing by one minus the sum of the autoregressive coefficients. This is identical to the process used for the U.S.

[38]Exchange rates circa 2006 placed a ten to fifteen percent premium on the U.S. dollar, translating to 1.3 to 1.4 billion USD.

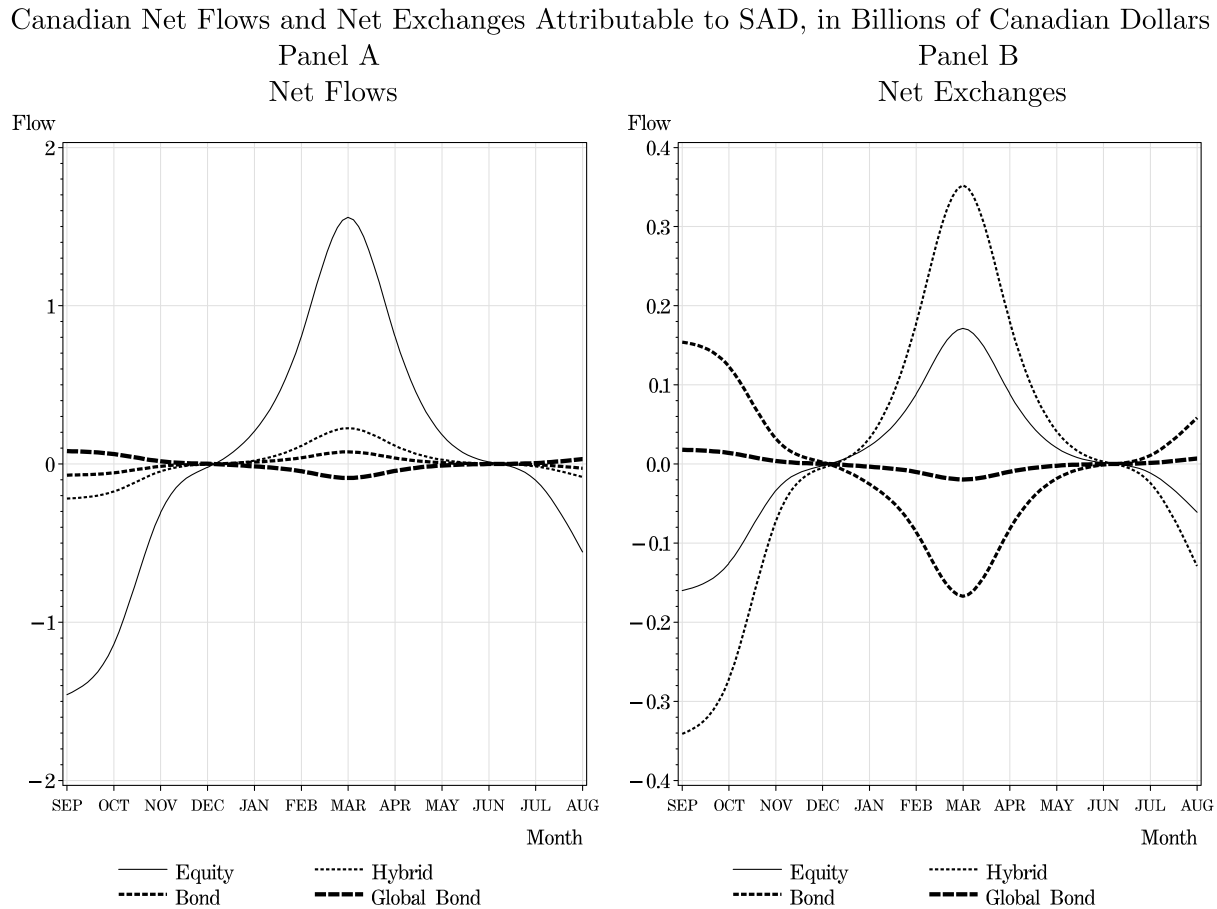

Figure 8: This figure reports the monthly net flows and net exchanges due to SAD, in billions of Canadian dollars, for equity, hybrid, fixed income and global fixed income funds, for 2006, provided by the Investment Funds Institute of Canada. See Appendix Cfor the model used to produce the economic impact of SAD on net flows.

compares to peak annual flows in U.S. equity funds of 10 to 15 billion USD, as shown in Panels A and B of Figure 5. The Canadian equity flows are roughly 150 percent of the U.S. equity flows on a per capita basis, consistent with SAD impacting flows more strongly in Canada.) The Canadian bond sector net flows attributable to SAD peak around plus-or-minus one hundred million dollars. The bond flows are proportionally smaller for Canada versus the U.S., but this reflects the smaller size of this fund category relative to the money market fund class in the U.S. and perhaps the poorer match of this asset class as a safe haven for investors than is the money market in the U.S.

Panel B contains a plot of the oscillation in net exchanges. Now we see that both bond asset class categories display opposing movements relative to the equity and hybrid asset classes. The U.S. equity net exchanges oscillate approximately plus-or-minus four billion dollars over the seasons, circa 2006, and the U.S. money market and government bond fund classes vary seasonally by roughly plus-or-minus one billion dollars, in opposition to equity flows. In contrast, the annual variation attributable to SAD for Canadian equity and hybrid funds peak around plus-or-minus half a billion dollars, and the global bond and bond fund classes in Canada vary by roughly plus-or-minus 0.2 billion dollars. These are relatively large net exchanges compared to the U.S. when considering the economy and population base of the U.S. are roughly 11 times larger than Canada's.[39]

In terms of coefficient estimates (which are tied directly to percentage exchanges and thus do not need to be adjusted for the different population sizes of the two countries), we see again larger proportional impacts in Canada, for the most part. The average $\hat{OR_t}$ value for U.S. equity and hybrid fund class net exchanges (from Table V) is approximately -0.08 while the average onset/recovery coefficient for Canadian equity and hybrid fund classes net exchanges is approximately -0.15 (from Table VII). The U.S. government bond and money market fund class net exchanges onset/recovery coefficient is approximately 0.18 (again from Table V) compared to the Canadian bond and global bond fund class net exchanges average coefficient of 0.45 (again from Table VII). That is, for both risky asset class net exchanges and safe asset class net exchanges, we see approximately double the movement in Canada that we see in the U.S.

VII Australian Flows

In this section, we test whether the relation of mutual fund flows to the seasonal onset and recovery from SAD is similar in 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.[40] We aim to rule out the possibility that our seasonal 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.

[39] Robustness checks exploiting the moment condition that the net exchanges sum to zero do not result in qualitative changes to our results.

[40] Note that the Australian population centroid is roughly at the latitude of Sydney, 34 degrees south. See Hugo (1999).

Specifically, we examine net 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 identify the SAD effect on flows, independent of the actual calendar month.

We obtained end-of-month total net assets (TNA) and estimated net flows from Morningstar for all Australian-domiciled mutual funds with an Australian equity focus for the period January 1991 to December 2006.[41] 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, 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 (equivalent to roughly 1.2 billion 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 U.S. equity mutual fund market as of December 31, 2006.

We report summary statistics on the Australian net flows, cumulated returns ($R_{i,t}^{CapGains}$) and returns over the past 12 months (R^{Year}) in Table VIII . R^{Year} is expressed as a monthly mean return and $R_{i,t}^{CapGains}$ equals the cumulated return to holding the fund from the previous year's July 1 (the start of the tax year in Australia) until month $t-1$.[42] The mean equity net flow is around half a percent

[41] Although earlier data are available, the number of funds in the database is well below 100 prior to 1991. Unfortunately, net exchanges are not available.

[42] This definition of $R_{i,t}^{CapGains}$ is most directly comparable to the Canadian definition of this variable, taking on non-zero

of TNA, and the standard deviation is almost 0.6. The return-chasing proxy for Australian equity flows, R^{Year}, and the capital gains overhang proxy, $R_{i,t}^{CapGains}$, behave similarly to the U.S. and Canada counterparts.

In Figure 9 we informally consider seasonal patterns in investor net flows associated with these Australian equity funds. More formal regression analysis follows. Consider first Panel A, in which the thick solid line represents the average monthly equity net flows. The equity net flows appear noisier than their U.S. counterparts in Figure 2. The average fitted values implied by the onset/recovery coefficient from estimating a regression model we introduce below (Equation (4)) are represented by a dashed line with diamonds. Panel B is identical to Panel A with the only difference being the dashed line with diamonds in Panel B represents the average fitted values implied by the full regression model (not just that implied by the coefficient estimate on onset/recovery).

The conditional seasonal patterns in equity fund net flows arising from that estimation are consistent with SAD having an impact on flows and the pattern is the reverse of U.S. and Canadian equity fund flows. We see conditional 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 U.S. and Canadian equity fund flows, but six months out-of-phase. Overall, the lower-than-average conditional flows in the summer/fall and higher-than-average conditional flows in the 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 U.S. The thin dotted lines surrounding the thick solid line are the 90% confidence interval around the monthly equity net flows. Compared to the U.S. flow data, the evidence shows less statistically significant unconditional seasonality, with only 4 months exhibiting

values for all months of the year except the first month of the tax year, July in Australia. The variable equals zero in July by construction. We specify $R^{CapGains}$ in this manner for Australia since, unlike the U.S., the start of the Australian tax year for mutual funds aligns with the overall start of the tax year. Our primary results are robust to excluding this capital gains variable from our model.

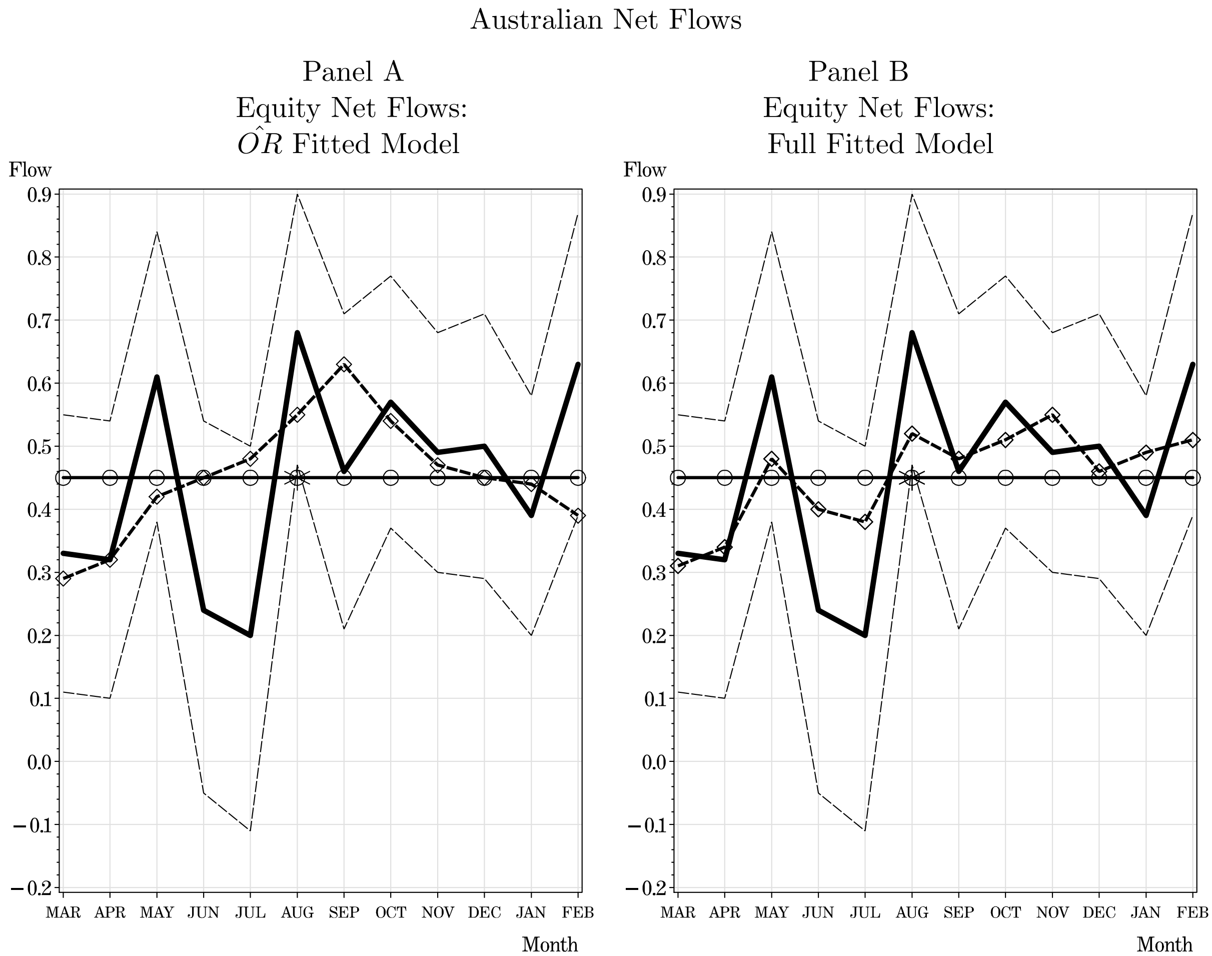

Figure 9: Panels A and B contain monthly average **Australian equity** aggregate fund flows as a proportion of prior-month Australian equity fund TNA, indicated with a thick solid line, and a 90% confidence interval around the monthly means (shown with thin dashed lines). Note that these plots start with the month of March, the first month of fall in Australia, to align the seasons relative to the plots for Canada and the U.S. The annual average flow is represented by a solid line horizontal with circles, and an x marks cases where the average return falls outside of the confidence interval. The dashed line with diamonds in Panel A represents the average fitted values implied by the onset/recovery coefficient from estimating Equation (4) and in Panel B represents the average monthly fitted values implied by the full set of coefficient estimates from estimating Equation (4).

significant evidence of monthly seasonality.

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

$$\begin{aligned} NetFlow_t &= \mu + \mu_{\hat{OR}_{South}} \hat{OR}_{South_t} + + \mu_{R^{Year}} R_t^{Year} + \mu_{CapGains} R_t^{CapGains} \\ &+ \rho_1 NetFlow_{t-1} + \rho_2 NetFlow_{t-2} + \rho_3 NetFlow_{t-3} \\ &+ \rho_6 NetFlow_{t-6} + \rho_{12} NetFlow_{t-12} + \epsilon_t, \end{aligned} \quad (4)$$

where i references the equity 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 U.S. counterpart to align with the southern hemisphere seasons, and $R_{i,t}^{Year}$ is the return to the equity fund asset class over the prior 12 months (*i.e.,* from month $t-13$ through month $t-1$), included to control for return-chasing flows. $R_{i,t}^{CapGains}$ is included to control for the influence of capital gains overhang on flows. $R_{i,t}^{CapGains}$ equals the cumulated return to holding the fund from the previous July 1 (the start of the tax year in Australia) until month $t-1$ (which equals zero for July). We are not able to obtain Australian savings-rate or mutual fund family advertising data.

We present estimation results for Equation (4) in Table IX. The model, while more parsimonious than that estimated for U.S. 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 U.S., unadjusted equity fund flows in Australia show strong positive autocorrelation. Similar to the SAD effect for U.S. equities, the sign of the SAD onset/recovery variable is significantly negative (recall that we are using a southern hemisphere version of the SAD variable, so that we expect to find the same sign for equity funds in Australia as we saw for equity funds in the U.S.). Further, the magnitude is economically meaningful and similar to our findings for U.S. funds: the coefficient value of -0.435 corresponds to a 43.5 basis point impact per unit of the SAD variable, and the SAD variable varies between roughly plus and minus 0.4. This translates into roughly 17 basis points of variation in flows in either direction associated with SAD. We also find strong evidence of return chasing, with lagged returns positively and statistically significantly inflating flows, but we see little impact from capital gains.

Overall, our model does a reasonably good job fitting seasonality in the Australian flow data. Figure 9, Panel B, presents the average fitted values from regressing net flows on the onset/recovery variable, the return-chasing variable, and autocorrelation terms, displayed by the dashed line with diamonds. Once again, the thick solid line represents the average monthly equity net flows. We see the fitted value tracks the monthly patterns in realized net flows fairly well, in particular

Australian Time Series of Net Flows &
Net Exchanges Attributable to SAD, in Billions of Australian Dollars

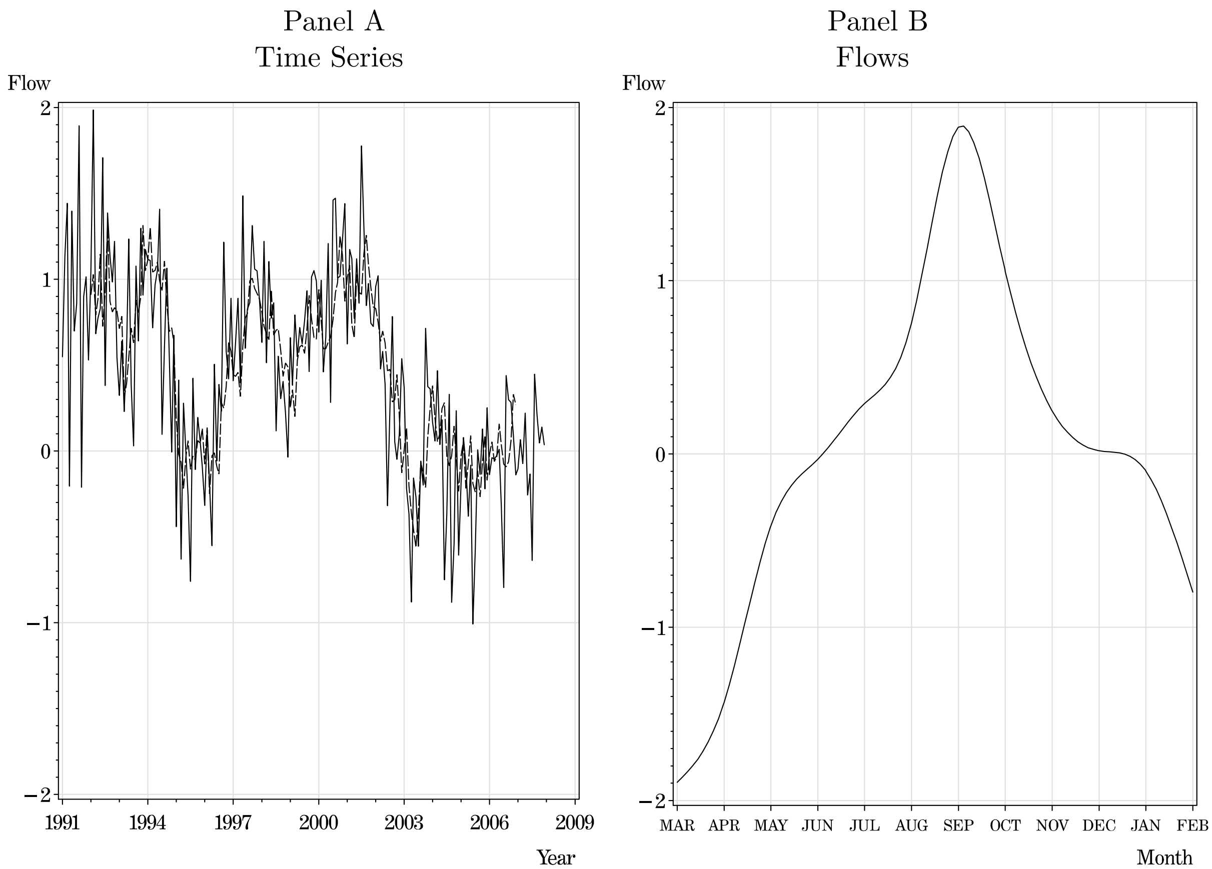

Figure 10: Panel A reports the monthly net flows due to SAD, in billions of AUD, for equity funds, for 2006. Panel B contains the time series of monthly **Australian equity** aggregate fund flows as a proportion of equity TNA, indicated with a solid line, and the monthly fitted values from estimating Equation (4) indicated with a dashed line. The data on equity fund flows, provided by Morningstar, span January 1 1991 through December 31 2007. The model is estimated over the period January 1992 through December 2006, hence the fitted series starts later and ends earlier than the realized series in the plot.

capturing variation around the end of the tax year that the SAD onset/recovery variable alone cannot capture in Panel A.

The *time-series* fit of the model is shown in Figure 10, Panel A. The model fit is relatively consistent over the sample, with the largest oscillations occurring around the end of the Australian 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. In Panel B, we summarize the average economic impact from flows associated with SAD for Australian equity funds, for 2006, with the thin line representing flows due to SAD.[43] Naturally the flows are much smaller in magnitude

[43]To estimate the long run impact in the setting of a model with autoregressive terms we inflate the immediate impact by dividing by one minus the sum of the autoregressive coefficients. This is identical to the process used for the U.S. and Canada.

than the corresponding flows for the U.S., ranging between outflows and inflows of approximately 1.9 billion AUD (roughly 1.5 billion USD in 2006). Since the U.S. economy is roughly 15 times larger than Australia's, the size-adjusted equity flows for Australia are very similar to the U.S., albeit slightly larger. In terms of SAD onset/recovery coefficient estimates, the estimate for Australian equity net flows is approximately -0.435 (from Table IX), for U.S. equity net flows it is -0.234 (from Table IV), and for Canadian equity net flows it is -0.514 (from Table C-III in Appendix C).

VIII Robustness of Results

We conducted a variety of robustness tests in addition to those described in the appendices. 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 (flows were estimated from returns and total net assets of funds). Second, we found virtually identical results for the U.S. when we excluded the first few years or the first half of our sample. Third, the ICI implemented changes in their data collection practices in January 1990, an artifact of which is outliers in the flow and returns data in that year. As a result, we explored omitting 1990 from our sample, which produced no qualitative changes in our results. Fourth, in Appendix B we show that our U.S. results are robust to estimating a model that excludes lags of the dependent variable. Fifth, we imposed a moment condition on flows due to SAD (and exchanges due to SAD) 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. Sixth, we experimented with slight augmentations to the model, including a dummy variable for the month of the new tax year (January for the U.S. and Canada, July for Australia), a dummy variable to allow a reversal of flows from December to January (for the U.S. and Canada, from June to July for Australia) related to tax-year rebalancing, and a dummy variable to allow a reversal of flows from October to November for the U.S. These produced no qualitative differences to our results on SAD. Seventh, we used seemingly unrelated regression techniques to estimate our system of equations, with MacKinnon and White (1985) heteroskedasticity-robust standard errors and sufficient lags to control for autocorrelation. This approach yields very similar results to GMM for both significance and magnitude of SAD effects. Eighth, in Appendix A we show that our results are robust to a less coarse classification of the thirty categories into nine asset classes. And in unreported results we find our results are robust to use of the full set of thirty-three categories provided by ICI. Ninth, for the Canadian data, we estimated our flows models on the completely disaggregated series of 10 funds. We found strong evidence consistent with SAD onset/recovery impacting returns in this more granular view of the U.S. and Canadian data. Tenth, in the main analysis, we end our U.S., Canadian, and Australian samples uniformly in December 2006 to avoid possible contamination from the financial crisis. In robustness checks, we extended the sample end points to include the most recent set of data available. Our findings with respect to the influence of onset/recovery on flows were qualitatively unchanged.

We also 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 cumulate capital gains for year t from the the previous year $t-1$ November (since the end-of-year for mutual funds is October). The value of the proxy for November and December in each case is the cumulated gains from the previous year's November to the current year's October. Depending on which proxy we employ in a particular model, the value of the proxy for January through 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.[44] We develop

[44]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) accumulated capital gains, 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

two capital gain measures using ICI data: a simple measure equal to the change in TNA, adjusted for inflows, and this simple measure less all distributions (as distributions tend not to 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 for 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 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.

Finally, we explored different proxies for return chasing, including a one month lagged return or a one quarter return moving average rather than a one year moving average. These model permutations produced no qualitative differences to our core

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.

result of a strong SAD seasonal in mutual fund flows.

IX Conclusion

In this paper, we document 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 somewhere between one and then percent of the population severely (depending on location and the diagnostic criteria used to test for SAD) 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, directly measured by incidence, to seasonal patterns in directly measured investment quantities.

Specifically, we find that net flows as well as net exchanges (a measure of investor sentiment studied by Ben-Rephael, Kandel, and Wohl 2011a, 2011b) 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/exchanges 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 study of international fund data, including Canada (a more northerly country where flows exhibit stronger seasonal variation, consistent with the greater prevalence of SAD documented in Canada) and Australia (a southern hemisphere country where the seasonal flow pattern is six months out-of-phase, as are the seasons).

The seasonal flows associated with SAD are economically large, representing tens of billions of dollars. These large flows are consistent with the SAD-related stock and bond returns documented by Kamstra, Kramer, and Levi (2003, 2011a) 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. Of course, as the seasons continue their cycle independently of financial markets, no level of risk aversion should occupy a favored "normal" status. This is an important lesson for any research where outcomes are sensitive to the specific assumptions made about risk aversion.

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

This table reports seasonal patterns in capital gains and dividend distributions among all mutual funds over the 1984 to 2007 period. To compute the percent of capital gains distributed 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 value of capital gains distributions occurring during that month (across all years) by the total value of capital gains distributions across all months. The column on the left presents these percentages, while the column on the right 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.

Average Percentage Taxable Distributions (Percent of Total Value of Distributions, by Month)

Month	Capital Gains	Taxable Dividend
January	1.1	6.9
February	0.9	7.0
March	2.4	8.9
April	1.1	7.3
May	1.5	7.2
June	3.8	9.3
July	1.9	7.5
August	1.8	7.3
September	2.2	9.3
October	1.6	7.7
November	9.8	7.6
December	72.0	14.1

Table II: Classification of Funds

In this table we map funds from thirty investment objective categories into a smaller set of 5 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 III: Summary Statistics on Monthly Percentage Asset Class Net Exchanges, Explanatory Variables, and Associated Returns to Holding These Funds

In this table we present summary statistics on monthly fund percentage net flows, percentage net exchanges, explanatory variables, and returns over January 1985 through December 2006, for a total of 264 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 in Panel D are in excess of the 30-day T-bill rate, with the 30-day T-bill rate available from CRSP. $R^{CapGains}$ is our capital gains proxy. For the months November and December, $R^{CapGains}$ equals the cumulated return to holding the fund from the previous year's November 1 (the start of the tax year for U.S. mutual funds) to the current year's October 31. $R^{CapGains}_{i,t}$ is set to zero in all months other than November and December. R^{Year} is the one-year moving average of fund percentage returns, to capture return chasing. The advertising variable is monthly print advertisement expenditures by mutual fund families, detrended by dividing by the previous year's total advertisement expenditure, resulting in a proportion. The advertising data originate from Gallaher, Kaniel, and Starks (2006), Figure 3. Savings are based on real disposable income and expenditures as a percent of real disposable income, annualized, obtained from the Bureau of Economic Analysis. 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/recovery 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. We use the CRSP value-weighted total market return, including dividends for our market return. The instruments used for the SAD regression are the onset/recovery variable, a constant, and one lag of each excess return. 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: Asset Class Percentage 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 Percentage 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 III continues on next page

Table III, 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: Asset Class 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***	-0.713
Corporate Fixed Income	0.396	1.30	-2.91	6.65	0.298	1.59	0.118***	0.111
Government Fixed Income	0.068	1.09	-3.65	3.55	-0.258	0.71	0.023*	0.694***
Money Market	0.125	0.91	-2.75	5.98	1.317	7.74	-0.000	0.314**

Panel E: Asset Class Net Flow Correlations

Asset Class	Equity	Hybrid	Corporate Fixed Income	Government Fixed Income
Hybrid	0.638***	—	—	—
Corporate Fixed Income	0.327***	0.483***	—	—
Government Fixed Income	0.220***	0.507***	0.761***	—
Money Market	-0.155**	-0.130**	0.017	-0.058

Panel F: Asset Class Net Exchange Correlations

Asset Class	Equity	Hybrid	Corporate Fixed Income	Government Fixed Income
Hybrid	0.337***	—	—	—
Corporate Fixed Income	0.231***	0.192***	—	—
Government Fixed Income	0.217***	0.155**	0.615***	—
Money Market	-0.750***	-0.400***	-0.487***	-0.518***

Table IV: Regression Results for Asset Class Net Flows

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

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

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 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 $4(T/100)^{2/9}$. We use the full set of explanatory variables as instruments for the regression. 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**

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 V: 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:

$$\begin{aligned} NetExchange_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,Ads}Ads_t + \mu_{i,R^{Year}}R_{i,t}^{Year} + \mu_{i,CapGains}R_{i,t}^{CapGains} \\ &+ \rho_{i,1}NetExchange_{i,t-1} + \rho_{i,3}NetExchange_{i,t-3} \\ &+ \rho_{i,6}NetExchange_{i,t-6} + \rho_{i,12}NetExchange_{i,t-12} + \epsilon_{i,t}. \end{aligned} \tag{2}$$

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 $4(T/100)^{2/9}$. We use the full set of explanatory variables as instruments for the regression. 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	0.035	0.022*	0.248***	0.055**	-0.105***
	(1.50)	(1.69)	(7.38)	(2.20)	(-4.85)
$\mu_{\hat{OR}}$	-0.164***	0.018*	-0.095***	0.092***	0.245***
	(-6.52)	(1.66)	(-3.28)	(3.86)	(9.98)
μ_{Ads}	-0.058**	-0.014	-0.332***	-0.135***	0.140***
	(-2.47)	(-1.10)	(-10.4)	(-5.87)	(6.54)
μ_{Year}	-0.009***	-0.017***	0.074***	0.046***	0.013
	(-4.49)	(-6.23)	(6.17)	(4.47)	(1.63)
$\mu_{CapGains}$	0.004***	0.001***	0.001	0.005***	-0.003***
	(8.31)	(2.66)	(1.09)	(5.02)	(-3.66)
ρ_1	0.055***	0.597***	0.207***	0.255***	0.151***
	(6.68)	(49.69)	(16.09)	(19.60)	(14.48)
ρ_3	0.173***	0.186***	0.053***	0.025**	0.060***
	(20.44)	(15.16)	(4.03)	(2.27)	(7.55)
ρ_6	0.067***	0.123***	-0.043***	0.123***	0.195***
	(8.40)	(8.95)	(-3.34)	(12.22)	(19.21)
ρ_{12}	0.024**	-0.035***	-0.094***	-0.072***	0.014
	(2.52)	(-3.71)	(-8.06)	(-7.07)	(1.57)
R^2	0.0616	0.6353	0.0873	0.1451	0.1087
AR(12)	13.86	11.72	20.25*	12.64	10.10
ARCH(12)	13.42	18.78*	20.86*	25.71**	54.35***

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	211.2** [5]
$\hat{OR}$ jointly equal across asset classes	118.9** [4]
Test of Over-Identifying Restrictions	45.4 [120]

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

In this table we present summary statistics on monthly fund percentage net flows, percentage net exchanges, explanatory variables, and returns over January 1992 through December 2006, for a total of 180 months. Flows data are from the Investment Funds Institute of Canada (IFIC), and returns were calculated using fund flow and total net asset changes available from the IFIC. The returns are in excess of the 30-day T-bill rate, available from CRSP. $R^{CapGains}$ is our capital gains proxy and equals the cumulated return to holding the fund from the previous January 1 (the start of the tax year for mutual funds in Canada) to the month $t-1$, and 0 for January. Unlike the U.S., mutual funds in Canada did not face the U.S. Tax Reform Act of 1986, and tax reporting on capital gains follows the tax year, January through December. R^{Year} is the one-year 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/recovery 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. We use the CRSP value-weighted total market return, including dividends for our market return. The instruments used for the SAD regression are the onset/recovery variable, a constant, and one lag of each excess return. 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: Asset Class Percentage Net Exchanges

Index	Mean	Std	Min	Max	Skew	Kurt
Equity	0.039	0.30	-1.29	1.25	0.258	3.68
Hybrid	0.118	0.43	-2.65	1.64	-1.583	11.47
Fixed Income	-0.157	0.51	-2.22	1.73	-0.379	3.02
Global Fixed Income	-0.316	1.07	-6.30	3.32	-1.761	10.62

Panel B: Explanatory Variables

Index	Mean	Std	Min	Max	Skew	Kurt
Equity Fund Specific:						
$R^{CapGains}$	2.059	7.41	-19.43	26.07	0.075	1.30
R^{Year}	0.831	1.45	-2.59	6.12	1.107	2.96
Hybrid Fund Specific:						
$R^{CapGains}$	6.324	10.32	-9.81	40.50	1.398	1.85
R^{Year}	1.067	1.10	-0.87	4.21	0.936	0.83
Fixed Income Fund Specific:						
$R^{CapGains}$	0.802	4.41	-15.11	8.37	-1.871	5.01
R^{Year}	0.371	0.57	-1.18	2.50	0.676	4.74
Global Fixed Income Fund Specific:						
$R^{CapGains}$	0.333	8.46	-26.88	20.05	-1.124	3.04
R^{Year}	0.787	1.79	-2.53	7.64	2.308	7.31

Panel C: Asset Class Excess Returns

Index	Mean	Std	Min	Max	Skew	Kurt	Beta	SAD
Equity	0.301	3.41	-15.45	9.10	-0.702	1.74	0.656***	-0.7773
Hybrid	0.684	3.68	-9.97	33.77	4.563	38.62	0.404***	-0.3750
Fixed Income	-0.025	1.39	-15.46	3.17	-7.729	84.86	-0.000	0.6039***
Global Fixed Income	0.105	2.98	-26.45	16.92	-3.047	39.75	-0.119***	1.8565***

Panel D: Asset Class Net Exchange Correlations

Asset Class	Equity	Hybrid	Fixed Income
Hybrid	-0.160**	—	—
Fixed Income	-0.806***	-0.127*	—
Global Fixed Income	-0.394***	0.148**	0.267***

Table VII: Regression Results for Canadian 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 based on Canadian data:

$$\begin{aligned} NetExchange_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \rho_{i,1}NetExchange_{i,t-1} + \rho_{i,3}NetExchange_{i,t-3} \\ &+ \rho_{i,6}NetExchange_{i,t-6} + \rho_{i,12}NetExchange_{i,t-12} + \epsilon_{i,t}. \end{aligned} \quad (3)$$

The data span January 1992 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 4 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 three 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 $4(T/100)^{2/9}$. We use the full set of explanatory variables as instruments for the regression. 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	Fixed Income	Global Fixed Income
μ	0.016**	-0.016**	-0.108***	-0.251***
	(1.98)	(-2.40)	(-7.02)	(-7.20)
$\mu_{\hat{OR}}$	-0.148***	-0.150***	0.339***	0.563***
	(-3.86)	(-4.32)	(4.69)	(4.65)
$\mu_{R^{CapGains}}$	0.001*	-0.002**	-0.005**	-0.004
	(1.79)	(-2.39)	(-2.16)	(-1.52)
$\mu_{R^{Year}}$	0.007*	0.060***	0.035**	0.072***
	(1.77)	(5.44)	(2.54)	(7.28)
ρ_1	0.209***	0.455***	0.266***	0.256***
	(7.50)	(14.34)	(8.51)	(10.17)
ρ_3	0.067***	0.153***	0.064***	0.069***
	(4.05)	(7.38)	(3.21)	(4.43)
ρ_6	0.013	0.035**	0.069***	0.031
	(0.68)	(2.48)	(2.95)	(1.29)
ρ_{12}	-0.070***	0.082***	-0.057**	-0.032*
	(-4.02)	(4.89)	(-2.32)	(-1.74)
R^2	0.0714	0.4048	0.1104	0.1071
AR(12)	22.61**	8.46	24.85**	7.02
ARCH(12)	13.89	5.01	9.71	33.48***

Panel B: Joint Tests on Onset/Recovery Coefficient Estimates

Joint Tests Across Indices	χ^2 [degrees of freedom]
$OnsetofSAD_t$ jointly equal to 0 across series	50.6*** [4]
$OnsetofSAD_t$ equivalent across series	50.5*** [3]
Test of Over-Identifying Restrictions	38.6 [72]

Table VIII : Summary Statistics & Regression Results for Australian Equity Fund Net Flows

In this table we present summary statistics on Australian monthly percentage net flows and explanatory variables for January 1992 through December 2006. Net 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. $R^{CapGains}$ is our capital gains proxy and equals the cumulated return to holding the fund from the previous July 1 (the start of the tax year in Australia) to the month $t-1$, and 0 for July. 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
Equity Percentage Net Flow	0.457	0.59	-1.01	1.98	-0.143	-0.38
$R^{CapGains}$	6.060	8.72	-11.55	32.60	0.487	-0.25
R^{Year}	1.111	0.93	-1.52	3.96	-0.221	0.53

Table IX: Regression Results for Australia Equity Fund Net Flows

In this table we report coefficient estimates from estimating the following regression with GMM using Australian data:

$$\begin{aligned} NetFlow_t &= \mu + \mu_{\hat{OR}_{South}} \hat{OR}_{South_t} + + \mu_{R^{Year}} R_t^{Year} + \mu_{CapGains} R_t^{CapGains} \\ &+ \rho_1 NetFlow_{t-1} + \rho_2 NetFlow_{t-2} + \rho_3 NetFlow_{t-3} \\ &+ \rho_6 NetFlow_{t-6} + \rho_{12} NetFlow_{t-12} + \epsilon_t. \end{aligned} \tag{4}$$

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 $4(T/100)^{2/9}$. We use the full set of explanatory variables as instruments for the regression. 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	-0.140**
	(-2.20)
$\mu_{\hat{OR}_{South}}$	-0.435***
	(-2.82)
$\mu_{R^{Year}}$	0.106**
	(1.99)
$\mu_{R^{CapGains}}$	0.005
	(0.78)
ρ_1	0.129**
	(2.50)
ρ_2	0.272***
	(3.70)
ρ_3	0.264***
	(3.81)
ρ_6	0.131*
	(1.65)
ρ_{12}	0.153**
	(2.55)
R^2	0.578
AR(12)	13.3
ARCH(12)	12.5

Appendix A: Alternate Classification of U.S. Funds

As a supplement to studying the five asset classes, we explored a less coarse classification of the ICI fund categories. In Table A-I we map the 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". "Government fixed income" is split into "munis," "medium and short-term government," and "general-term government." The "money market" class remains as previously defined. Table A-II contains summary statistics on the net flows, excess returns, and other variables for these nine asset classes, as well as correlations between net flows across classes.

In Table A-III, we present results from estimating Equation (5) as a system of nine equations (across the expanded set of nine asset classes) using GMM and HAC standard errors. (In this model we excluded lagged dependent variables, but our results are very similar for a model with sufficient lags to purge autocorrelation. The model is fully detailed in Appendix B.) 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 estimates are negative and significant for the risky equity, safe equity, hybrid, and U.S. corporate bond asset classes, with the equity case showing the largest economic magnitude of these four. We find positive and significant coefficient estimates for the global corporate bond and money market classes. Once again, the money market coefficient estimate is the largest of all considered. 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.

Table A-I: Classification of Funds into Enlarged Set of Nine Asset Classes

In this table we map funds from thirty investment objective categories into a set of nine 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," "U.S. 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 Nine)
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	U.S. Corporate Bond
15	Corporate - Intermediate	U.S. Corporate Bond
16	Corporate - Short Term	U.S. Corporate Bond
17	High Yield	U.S. 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	U.S. 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 A-II: Summary Statistics on Monthly Percentage Flows for Nine Asset Classes

This table contains summary statistics on monthly percentage fund flows, explanatory variables, and returns over January 1985 through December 2006, for a total of 264 months for 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 in Panel C are in excess of the 30-day T-bill rate, with 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/recovery variable, each estimated separately of the other. These coefficients are produced in a systems equation estimation using GMM and HAC 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 $4(T/100)^{2/9}$. For instruments for the CAPM regression, we use the market return, a constant, and one lag of each excess return. We use the CRSP value-weighted total market return, including dividends for our market return. For instruments for the SAD regression, we use the onset/recovery variable, a constant, and one lag of each excess return.

Panel A: Asset Class Fund Percentage Net 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
U.S. 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

Panel B: 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
U.S. 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

Table A-II continues on next page

Table A-II, Continued

Panel C: 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**
U.S. 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**

Panel D: Asset Class Net Flow Correlations

Asset Class	Risky Equity	Safe Equity	Corp. Hybrid	Corp. Bond - U.S.	Bond - Global	Govt. General	Govt. Med., Short	Munis
Safe Equity	0.634***	—	—	—	—	—	—	—
Hybrid	0.437***	0.747***	—	—	—	—	—	—
Corp. Bond - U.S.	0.233***	0.518***	0.525***	—	—	—	—	—
Corp. Bond - Global	0.029	0.214***	0.131**	0.220***	—	—	—	—
Govt. Bond - General	-0.060	0.254***	0.405***	0.579***	0.188***	—	—	—
Govt. Bond - Med., Short	0.015	0.300***	0.446***	0.704***	0.233***	0.895***	—	—
Munis	0.131**	0.453***	0.536***	0.797***	0.341***	0.708***	0.807***	—
Money Market	-0.124**	-0.157**	-0.130**	-0.095	0.046	-0.102*	-0.034	-0.023

Table A-III: Regression Results for Enlarged Set of Nine Asset Class: Net Flows

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

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \mu_{i,Savings}Savings_{i,t} + \epsilon_{i,t}. \end{aligned} \tag{5}$$

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 nine 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 $4(T/100)^{2/9}$. We use the full set of explanatory variables as instruments for the regression. 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 - U.S.	Corporate Bond - Global
μ	-0.401*	-2.563***	-6.338***	-6.405***	-26.61***
	(-1.66)	(-16.4)	(-23.2)	(-26.8)	(-31.0)
$\mu_{\hat{OR}}$	-0.838***	-0.504***	-0.308*	-0.468***	1.015**
	(-7.12)	(-5.00)	(-1.81)	(-4.30)	(2.21)
μ_{Ads}	-0.055	0.241***	-0.143	-0.755***	-1.410***
	(-0.54)	(3.10)	(-0.99)	(-5.61)	(-3.19)
$\mu_{R^{Year}}$	0.168***	0.233***	0.709***	1.089***	0.879***
	(12.25)	(25.72)	(20.70)	(31.11)	(17.51)
$\mu_{CapGains}$	0.003*	-0.006***	-0.004	-0.011***	-0.040***
	(1.91)	(-5.56)	(-1.05)	(-3.43)	(-5.63)
$\mu_{Savings}$	0.529***	1.742***	4.364***	4.637***	18.859***
	(4.01)	(18.42)	(25.52)	(32.79)	(34.85)
R^2	0.0928	0.2322	0.3122	0.468	0.0805
AR(12)	104.55***	213.18***	332.75***	105.96***	5.84
ARCH(12)	29.70***	105.64***	68.92***	47.30***	64.46***

Table A-III continues on next page

Table A-III, Continued

Panel B: Parameter Estimates and Diagnostic Statistics

Parameter or Statistic	Government General	Government Medium-, Short-Term	Munis	Money Market
μ	-18.18***	-8.261***	-6.103***	0.369
	(-23.7)	(-14.5)	(-19.6)	(0.70)
$\mu_{\hat{OR}}$	-0.024	-0.270	-0.197	1.385***
	(-0.09)	(-0.90)	(-1.31)	(6.76)
μ_{Ads}	-0.079	-0.805***	-0.368**	-0.583***
	(-0.27)	(-2.98)	(-2.53)	(-3.27)
$\mu_{R^{Year}}$	4.164***	3.416***	1.768***	0.789***
	(38.43)	(72.32)	(41.01)	(7.86)
$\mu_{CapGains}$	-0.031***	-0.019**	-0.008**	0.050***
	(-3.47)	(-2.52)	(-2.01)	(5.29)
$\mu_{Savings}$	10.859***	5.259***	4.036***	0.090
	(25.57)	(14.26)	(21.32)	(0.29)
R^2	0.5872	0.681	0.5608	0.0656
AR(12)	158.09***	299.44***	102.56***	56.26***
ARCH(12)	51.05***	94.27***	74.29***	52.51***

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	124.6*** [9]
$\hat{OR}$ jointly equal across asset classes	107.5*** [8]
Test of Over-Identifying Restrictions	51 [144]

Appendix B: A Model of Net Flows Excluding Lagged Dependent Variable Terms

We return to our original five asset classification of the thirty-three ICI fund categories, and explore the impact of excluding lagged dependent variables and instead adjust for autocorrelation with Hansen's (1982) GMM and Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) standard errors. The regression model we now estimate is as follows.

$$\begin{aligned} NetFlow_{i,t} &= \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,Ads}Ads_t + \mu_{i,R^{Year}}R^{Year}_{i,t} + \mu_{i,CapGains}R^{CapGains}_{i,t} \\ &+ \mu_{i,Savings}Savings_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{5}$$

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 1 (the start of the tax year for mutual funds) to the current year's October 31. $R^{CapGains}_{i,t}$ is set to zero in all months other than November and December. $Savings_{i,t}$ is personal savings, lagged one period. Personal savings is included as a control variable for investor liquidity needs, which might also affect fund flows in a seasonal way.

We estimate Equation (5) as a system of equations using Hansen's (1982) GMM and Newey and West (1987) HAC standard errors.[45] Results from estimating this set of equations are shown in Table B-I. In Panel A we present coefficient estimates and two-sided t-tests. Our use of HAC standard errors is consistent with the strong statistical evidence of autocorrelation. The bottom of Panel A contains the 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 summer/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 summer/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 summer/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 statistic 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, 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.[46] The goodness-of-fit test indicates that the over-identifying moment restrictions we use to estimate the model are not rejected.

[45] To calculate 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 includes the full set of explanatory variables. Specifically, for each equation we include $\hat{OR}_t$, Ads_t, $R^{Year}_{i,t}$, $R^{CapGains}_{i,t}$, and $Savings_t$.

[46] Hansen (1982) details conditions sufficient for consistency and asymptotic 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.

Consider now other coefficient estimates shown in Table B-I. 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.[47] The savings variable is strongly significantly positive for all classes of funds except the money market class, consistent with results throughout the paper.

[47] 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 market 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.

Table B-I: Regression Results for Asset Class Net Flows, No Controls for Autocorrelation

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

$$NetFlow_{i,t} = \mu_i + \mu_{i,\hat{OR}}\hat{OR}_t + \mu_{i,Ads}Ads_t + \mu_{i,R^{Year}}R_{i,t}^{Year} + \mu_{i,CapGains}R_{i,t}^{CapGains} + \mu_{i,Savings}Savings_{i,t} + \epsilon_{i,t}. \quad (5)$$

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 $4(T/100)^{2/9}$ We use the full set of explanatory variables as instruments for the regression. 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	-1.619***	-6.445***	-5.711***	-7.850***	0.053
	(-3.85)	(-8.23)	(-6.27)	(-5.56)	(0.05)
$\mu_{\hat{OR}}$	-0.599***	-0.283	-0.461	-0.406	1.341***
	(-2.95)	(-0.76)	(-1.62)	(-0.97)	(3.02)
μ_{Ads}	0.042	-0.253	-0.773***	-0.510	-0.643*
	(0.23)	(-0.85)	(-3.01)	(-1.13)	(-1.67)
μ_{Year}	0.215***	0.657***	0.964***	2.900***	0.584***
	(7.26)	(7.01)	(9.01)	(10.17)	(2.85)
$\mu_{Savings}$	1.242***	4.521***	4.255***	4.986***	0.441
	(5.08)	(9.12)	(7.76)	(5.84)	(0.65)
$\mu_{CapGains}$	-0.003	-0.009	-0.015*	-0.044**	0.074***
	(-1.03)	(-1.08)	(-1.81)	(-2.11)	(3.36)
R^2	0.1731	0.3094	0.4401	0.5966	0.0621
AR(12)	185.01***	331.35***	121.00***	214.00***	55.75***
ARCH(12)	64.15***	69.04***	38.29***	59.60***	52.81***

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	42.1 [40]

Appendix C: Details on Constructing Asset Classes for Canada and Results Based on Canadian Net Flows

We have constructed four broad categories of funds (equity, hybrid, fixed income, and global fixed income) from the 10 Investment Funds Institute of Canada (IFIC) categories of funds available. The 10 IFIC categories are listed in Table C-I, alongside the more detailed Canadian Investment Funds Standards Committee (CIFSC) categories. The IFIC asset classes included in our four broad categories are as follows. Our equity category includes "Global and International Equity", "Domestic Equity", "Sector Equity", and "U.S. Equity'.' Our hybrid category includes "Domestic Balanced", "Global Balanced" and "Specialty'.' Our fixed income category includes "Domestic Fixed Income" and "Money Market'.' Our global fixed income includes "Global and High Yield Fixed Income".

The "Global and International Equity" IFIC class includes Asia Pacific Equity, Asia Pacific ex-Japan Equity, Emerging Markets Equity, European Equity, Global Equity, Global Small/Mid Cap Equity, International Equity, and Japanese Equity. The "Domestic Equity" IFIC class includes Canadian Dividend and Income Equity, Canadian Equity, Canadian Focused Equity, Canadian Focused Small/Mid Cap Equity, Canadian Income Trust Equity, and Canadian Small/Mid Cap Equity. The "Sector Equity" IFIC class includes Financial Services Equity, Health Care Equity, Natural Resources Equity, Precious Metals Equity, Real Estate Equity, and Science and Technology Equity. The "U.S. Equity" IFIC class includes North American Equity, U.S. Equity, and U.S. Small/Mid Cap Equity. The "Domestic Balanced" IFIC class includes Canadian Equity Balanced, Canadian Fixed Income Balanced, and Canadian Neutral Balanced. The "Global Balanced" IFIC class includes 2010 Target Date Portfolio, 2015 Target Date Portfolio, 2020 Target Date Portfolio, 2020+ Target Date Portfolio, Global Equity Balanced, Global Fixed Income Balanced, Global Neutral Balanced, and Tactical Balanced. The "Specialty" IFIC class includes Alternative Strategies, and miscellaneous, including Geographic Equity, Commodity, Income and Real Property, Leveraged, Other, Sector Equity, and The "Domestic Fixed Income" IFIC class includes Canadian Fixed Income, Canadian Inflation Protected Fixed Income, Canadian Long Term Fixed Income, Canadian Short Term Fixed Income. The "Money Market" IFIC class includes the Canadian Money Market, the Canadian Synthetic Money Market, the U.S. Synthetic Money Market, and the U.S. Money Market. The "Global and High Yield Fixed Income" IFIC class includes Global Fixed Income and High Yield Fixed Income.

Table C-II contains summary statistics on monthly asset class net flows and personal savings (Panel A) and the correlation of flows across asset classes (Panel B). The remainder of our data are described in Table VI. The range of the data extends from January 1992 through December 2006. As previously mentioned, fund flows are reported as a proportion of a given fund's prior end-of-month total net assets.

In Panel A of Table C-II we can see that the mean monthly net flows range from just under 0.5 percent of TNA to a little over 1.5 percent per month. As with U.S. fund flows, equity asset class flows are less volatile than fixed income and show less evidence of skew and kurtosis. The hybrid asset class is the most fat-tailed and skewed. Savings are based on persons and unincorporated business, seasonally adjusted interpolated to monthly, obtained from Statistics Canada.[48] Savings rates are both higher and more volatile than we see in the U.S. Similar to U.S. flow correlations, the equity and fixed income classes all exhibit unconditional positive correlations, strongly statistically significant.

Using the Canadian flow data, we estimate Equation (1) as a system of equations using GMM and HAC standard errors. The results, presented in Table C-III are very similar to those for U.S. flows, Table IV, showing strong reverse seasonalities for risky versus safe asset classes, though the reversal is stronger for Canadian flows, with the $\mu_{\hat{OR}}$ coefficient estimate on the equity class more than double that seen for U.S. flows, and the safe end having similar flow impacts as measured by $\mu_{\hat{OR}}$. Again we see some avoidance of funds with capital gains exposure, (apart from equity funds; identical to the case for the U.S.), savings tend to increase flows, and there is evidence of some strong return-chasing behavior.

[48]The seasonally adjusted data are from CANSIM Table 3800004. In untabulated results we found very similar results using seasonally unadjusted savings rate data, also from CANSIM Table 3800004.

Table C-I
Mutual Fund Classes

IFIC Asset Class	CIFSC Category
Global and International Equity	Asia Pacific Equity
	Asia Pacific ex-Japan Equity
	Emerging Markets Equity
	European Equity
	Global Equity
	Global Small/Mid Cap Equity
	International Equity
	Japanese Equity
Domestic Equity	Canadian Dividend and Income Equity
	Canadian Equity
	Canadian Focused Equity
	Canadian Focused Small/Mid Cap Equity
	Canadian Income Trust Equity
	Canadian Small/Mid Cap Equity
Sector Equity	Financial Services Equity
	Health Care Equity
	Natural Resources Equity
	Precious Metals Equity
	Real Estate Equity
	Science and Technology Equity
U.S. Equity	North American Equity
	U.S. Equity
	U.S. Small/Mid Cap Equity
Domestic Balanced	Canadian Equity Balanced
	Canadian Fixed Income Balanced
	Canadian Neutral Balanced
Global Balanced	2010 Target Date Portfolio, 2015 Target Date Portfolio
	2020 Target Date Portfolio, 2020+ Target Date Portfolio
	Global Equity Balanced, Global Fixed Income Balanced,
	Global Neutral Balanced, Tactical Balanced
Specialty	Alternative Strategies
	Miscellaneous - Geographic Equity, Commodity,
	Income and Real Property, Leveraged ,
	Other, Sector Equity, Undisclosed Holdings
Domestic Fixed Income	Canadian Fixed Income
	Canadian Inflation Protected Fixed Income
	Canadian Long Term Fixed Income
	Canadian Short Term Fixed Income
Money Market	Canadian Money Market
	Canadian Synthetic Money Market
	U.S. Synthetic Money Market
	U.S. Money Market
Global and High Yield Fixed Income	Global Fixed Income
	High Yield Fixed Income

Table C-II: Summary Statistics

Panel A: Asset Class Percentage Net Flows and Personal Savings Data

Index	Mean	Std	Min	Max	Skew	Kurt
Equity	0.932	1.38	-0.61	5.87	1.648	2.28
Hybrid	1.476	2.46	-2.64	16.68	2.879	11.45
Fixed Income	0.494	1.88	-7.13	6.89	0.138	1.98
Global Fixed Income	1.503	4.76	-7.61	24.60	2.347	6.71
Savings	1.988	1.62	-1.10	6.77	0.386	-0.46

Panel B: Asset Class Net Flow Correlations

Asset Class	Equity	Hybrid	Fixed Income
Hybrid	0.711***	—	—
Fixed Income	0.286***	0.504***	—
Global Fixed Income	0.311***	0.599***	0.357***

Table C-III: Regression Results for Canadian Asset Class Net Flows

In this table we report coefficient estimates from jointly estimating the following regression for each of the asset classes in a GMM framework, using Canadian data as described in Section VI:

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

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. 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 $4(T/100)^{2/9}$. We use the full set of explanatory variables as instruments for the regression. 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 (t-test)	Hybrid (t-test)	Bond (t-test)	Global Bond (t-test)
μ	-0.148***	-0.238***	-0.068	-0.341**
	(-3.68)	(-5.30)	(-1.00)	(-2.50)
$\mu_{\hat{OR}}$	-0.514***	-0.083	-0.133	0.946***
	(-4.22)	(-0.74)	(-0.71)	(3.22)
$\mu_{R^{Year}}$	-0.010	0.400***	1.053***	0.947***
	(-0.51)	(8.37)	(10.00)	(21.50)
$\mu_{CapGains}$	0.020***	-0.026***	-0.058***	-0.056***
	(5.74)	(-5.46)	(-4.35)	(-6.41)
$\mu_{Savings}$	0.195***	0.157***	0.011	-0.027
	(7.72)	(6.08)	(0.36)	(-0.40)
ρ_1	0.521***	0.690***	0.566***	0.606***
	(18.82)	(42.59)	(28.15)	(28.72)
ρ_3	0.089***	0.005	-0.135***	-0.083***
	(3.69)	(0.49)	(-7.01)	(-4.90)
ρ_6	0.009	-0.003	0.083***	0.082***
	(0.46)	(-0.48)	(4.19)	(5.15)
ρ_{12}	0.083***	0.074***	-0.076***	0.143***
	(4.60)	(8.55)	(-4.34)	(8.76)
R^2	0.6135	0.6449	0.5054	0.7821
AR(12)	27.75***	12.33	32.80***	22.86**
ARCH(12)	41.76***	45.82***	22.70**	30.99***

Panel B: Joint Tests on Onset/Recovery Coefficient Estimates

Joint Tests Across Indices	χ^2 [degrees of freedom]
$\hat{OR}$ jointly equal to zero across sector funds	32.8*** [4]
$\hat{OR}$ jointly equal across sector funds	23.6*** [3]
Test of Over-Identifying Restrictions	38.4 [72]