Do Investors Care about Risk?
Evidence from Mutual Fund Flows

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Abstract:

Using an extensive database compiled from SEC N-SAR filings, we study how risk affects monthly flows to equity mutual funds over the period 1996 to 2009. Unlike most previous studies, we separately examine inflows, outflows, and net flows. We find that both retail and institutional investor inflows and outflows strongly chase past raw performance, but more importantly, they do so without regard to risk. This behavior appears to neither help nor harm investors, but it has significant implications for fund managers. Among other things, the well-documented inability of fund managers to produce significant abnormal returns may be due to incentives rather than lack of skill or market efficiency.

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1. Introduction

When making mutual fund investment decisions, do investors take risk into account? A central tenant in finance is that investors seek to maximize risk-adjusted, after-tax returns. Studies as early as Chevalier and Ellison (1997) document strong return chasing by mutual fund investors; however, little is known about whether investors seek to minimize risk in the process. Using an extensive database compiled from SEC N-SAR filings, we study monthly flows to equity funds over the period 1996 to 2009. Unlike most previous studies, we separately examine inflows, outflows, and net flows. We find clear evidence that investor inflows and outflows strongly chase past raw performance without regard to risk. In fact, the best performing funds are typically among the riskiest funds, so return chasing leads to apparent risk-seeking behavior for inflows. This behavior is particularly strong for retail investors, but return chasing is also prevalent for institutional investors.

The fact that risk is immaterial to the average mutual fund investor creates interesting incentives for fund managers. A number of studies indicate that fund managers generally are unable to produce positive, risk-adjusted returns. This finding is often cited as proof that managers lack skill or that markets are efficient (or both). However, this conclusion begs the question of whether managers are incentivized to produce risk-adjusted returns in the first place. Imagine a fund manager is considering two stocks, one that he expects to gain 10 percent versus a required return of 8 percent (i.e., an alpha of 2 percent) and another that he expects to gain 16 percent with a required return of 18 percent (i.e., an alpha of -2 percent). Based on the evidence in this paper, the manager is better served by producing raw returns, even at the expense of risk-adjusted performance. Given the incentives he faces, the fund manager should choose the value-destroying, higher raw return stock.

Orthodox theory suggests that the manager should purchase high alpha stocks regardless of their expected returns and then use leverage to obtain any desired risk/return profile. However, the use of leverage by mutual funds is miniscule. By the end of our sample period, 26 percent of our funds can, by charter, use leverage, but only 20 percent of these funds do. Put differently, 95 percent of equity mutual funds do not use leverage. Alternatively, fund managers could provide alpha to fund investors who could, in principle, use "homemade" leverage. We have no direct evidence on the use of leverage by fund investors, but we suspect the practice is uncommon.

Successful fund managers grow assets under management, which, as we show, is not the same thing as producing alpha. In addition to the fact that investors' flows respond to raw returns, we outline two further mechanisms that incent managers to focus on raw returns. First, raw returns are actually the most important source of growth in assets under management for most funds. Over the period we study, the average fund's annual net flow was only 0.60 percent of beginning-of-year assets under management, while the average fund's annual return was over five times larger (3.24 percent). Second, fund managers are often evaluated against index benchmarks such as the S&P 500 or style benchmarks such as large-cap growth on a raw, not risk-adjusted, basis.

We investigate whether return chasing is hazardous to investors' wealth. In the aggregate, investors do not benefit when they buy. Further, for the larger funds with the lion's share of assets and flows, outflows neither help nor harm. For smaller funds, outflows appear to avoid future underperformance, a "smart money" effect. However, we suggest an alternative explanation; namely, large outflows at a small fund may lead to subsequent underperformance at the expense of investors who remain in the fund. This view is consistent with the rationale provided by funds for the widespread use of short-term trading fees and the recent literature on asset "fire sales."

The remainder of this paper proceeds as follows. The next section reviews previous studies of fund manager performance and the flow/performance literature. Section 3 describes our sample and presents summary statistics on a number of variables. In Section 4, we analyze the determinants of fund flows, and we explore whether return chasing is harmful to fund investors. Section 5 discusses the implications of return chasing for mutual fund managers, and Section 6 concludes.

2. Background

Evidence of poor risk-adjusted performance for mutual funds goes as far back as Jensen (1968), but the issue has continued to attract research interest. The most recent studies continue to indicate that few, if any, managers are skilled (e.g., Fama and French, 2010). Furthermore, those managers that appear skilled in one year generally do not display persistent superiority (Carhart, 1997; Sapp and Tiwari, 2004). However, these same studies find evidence of persistent poor performance.

A number of papers have studied fund flow dynamics, but different models are used.[1] Table 1 provides a representative set of twenty-eight such studies and describes the variables used for performance measurement. Every model shows that greater performance (however defined) leads to greater cash flow, and poor performance leads to less cash flow. However, the reaction is asymmetric; the best funds get the lion's share of new money but the worst funds face only modest outflows. These studies evaluate monthly, quarterly, and annual cash flows. Modeling technology ranges from OLS and GLS to pooled regressions and panels. Despite these differences, the asymmetric nature of flow and performance is very robust.[2]

[1] For example, see Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), Zheng (1999), Del Guercio and Tkac (2002), Karceski (2002), Lynch and Musto (2003), Nanda, Wang, and Zheng (2004), Barber, Odean, and Zheng (2005), and Friesen and Sapp (2007).

[2] Besides typical fund and family characteristics (e.g., size, expenses, loads), there exist additional factors influencing flows. Del Guercio, Reuter, and Tkac (2010) find that a fund's target market (retail or insurance, for example) may make a fund's flows more or less sensitive to performance. Trend chasing may also determine a fund's flows, either because of

[Table 1 about here]

Two major explanations have been proposed for the flow/performance relationship. The first claims that a subset of investors has difficulty evaluating funds or transferring their cash flow between funds (Gruber, 1996). This "disadvantaged clientele" faces difficulty analyzing mutual funds and may not fully understand key aspects of the mutual fund industry.[3]

Some studies support the existence of a disadvantaged clientele. Fund flows are sensitive to front end loads and commissions (easily assessed information) but not as sensitive to operating expenses or marketing fees (Barber, Odean, and Zheng, 2005). Fund flows also appear to take declared benchmarks and fund names at face value, even though one-third of benchmarks are not correct for the funds' true styles and name changes have little impact on actual investment style (Cooper, Gulen, and Rau, 2005; Sensoy, 2009). Huang, Wei, and Yan (2007) model cash flows assuming investors have varying levels of participation costs, i.e., the cost of evaluating and investing in (or divesting out of) a mutual fund. Funds with high participation costs receive less cash flow, while funds with low participation costs have higher fees. Huang et al. demonstrate that low participation cost funds are more sensitive to performance, yielding a concentration of participation costs in funds with low cash flow. Similarly, Morningstar ratings—easily available data—impact fund flows (Del Guercio and Tkac, 2008; Reuter and Zitzewitz, 2010).

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news effects, sentiment, or other behavioral biases (Frazzini and Lamont, 2006; Massa and Yadav, 2010; Bailey, Kumar, and Ng, 2010). Reuter and Zitzewitz (2010) show that Morningstar ratings introduce discontinuities in the flow/performance relationship. The performance of the domestic equity market relative to other domestic asset types or foreign equity markets may also influence industry and fund flows (Karceski, 2002; Goetzmann, Massa, and Rouwenhorst, 2010; Chen, Goldstein, and Jiang, 2010). While flows decrease during poor performance, they increase again with a management change, even before the new manager's performance can be measured (Khorana, 2001; Bessler, Blake, Luckoff, and Tonks, 2010).

[3] Gruber (1996) also suggests the existence of a "smart clientele." Sapp and Tiwari (2004) show that most of the smart money results of Gruber (1996) disappear when momentum is included. Keswani and Stolin (2008) document smart money in both the US and the UK post-1994 even accounting for momentum, but Frazzini and Lamont (2006) show that buying the same stocks as funds with high flow leads to lower returns.

The second explanation for the performance-cash flow relationship is a rational investor story. Berk and Green (2004) develop a model with two important assumptions. First, some managers have skill. Second, skill is diminishing with fund size. When managers demonstrate alpha, they receive more cash flow. Greater cash flow causes diseconomies of scale, and the manager is no longer able to outperform. Hence, in equilibrium, no manager will demonstrate positive performance, but investor return chasing is entirely rational.

Support for Berk and Green's assumptions and model exist. Performance decreases as fund size increases, and it does so most sharply in funds that invest in small, illiquid stocks (Chen, Hong, Huang, and Kubik, 2004; Kacperczyk, Sialm, and Zheng, 2005). Similarly, the marginal returns to information acquisition and trading decrease with size (Indro, Jiang, Hu, and Lee, 1999). Kim (2010) shows that the convex relationship between returns and flow is greatly diminished during high volatility time periods, suggesting investors made a rational conclusion that performance in uncertain markets is more likely due to luck than skill.

Other studies use fund flows to measure the size effect. Bessler, Blake, Luckoff, and Tonks (2010) show that funds with good performance, but the least cash flow, outperform funds with both good performance and the most cash flow. Pollet and Wilson (2008) suggest that funds do not invest new money optimally. Funds only slowly diversify their holdings following a positive cash flow shock and tend to keep investing in the same assets. Pollet and Wilson argue that these funds miss out on diversification benefits as a result of their size and suggest that this failure to diversify is the source of diseconomies of scale.

Taking a different approach, Cohen, Polk, and Silli (2009) assume that the highest weighted stocks in a portfolio represent the manager's "best" ideas. These stocks significantly outperform the rest of the portfolio, suggesting that many of the holdings are not held to outperform but instead to remain fully invested in equity. Cohen et al. propose that the inclusion of non-performing stocks (diversification) is the result of scale problems. The literature currently disagrees as to whether diversification is good or bad for a fund. Baks, Busse, and Green (2006) show that concentrated funds perform better than broadly diversified funds but Sapp and Yan (2008) and Pollet and Wilson (2008) find that concentrated funds are no better (and perhaps worse) than diversified funds. Interestingly, Pollet and Wilson and Cohen et al. find different results regarding diversification but both claim to support the same theory.

In contrast, some find that the assumptions and predictions of Berk and Green are unsupported. Fama and French (2010) provide relatively strong evidence contrary to a central prediction. In Berk and Green's equilibrium, fund managers have zero alphas in their net returns, but their gross returns should have positive alpha to reflect skill prior to costs. Fama and French find instead that managers have negative alphas on net returns (though some funds have positive alpha in gross returns). Reuter and Zitzewitz (2010) also find weaker diseconomies of scale for funds facing flow shocks than assumed by Berk and Green.

Asymmetric return chasing by mutual fund investors creates interesting incentives for fund managers. Mutual fund manager compensation is usually tied to assets under management. Since performance attracts more cash to the fund, managers have an incentive to achieve superior returns. However, poor returns cause relatively little cash to leave the fund. Since poor performance has few consequences, there is a resulting agency conflict and a call option-like payoff (Chevalier and Ellison, 1997). Managers are not disciplined for low returns, which could induce fund managers to take on higher risks in the hope of achieving greater returns and greater compensation.

The convex flow/performance relation creates an implicit tournament for cash flow, where finishing at the top of the list matters the most (Brown, Harlow, and Starks, 1996). Depending on year-to-date performance, mutual fund managers may alter their portfolios more towards the end of the year to take on more or less risk, or they may show a general preference for risky stocks (Falkenstein, 1996; He, Ng, and Wang, 2004; Massa and Patgiri, 2009). The investment decisions become less about performance and more about increasing the probability of being a big "winner" in the yearly cash flow tournament. A tournament also implies that relative performance may matter more than absolute performance (having the highest return is different from having a high return).

Most empirical research focuses on implied net flows. However, inflows and outflows can provide additional insight into the flow-performance relationship. Recently, a small number of studies have examined gross flows mostly using data from SEC Form N-SAR. Edelen (1999) first examined N-SAR gross flows using a random sample of 166 funds over the period 1985-1990. He finds that median fund net cash flow is about 1 percent of assets over 6 months, but the median inflows and outflows were between 30 percent and 40 percent of assets. Greene and Hodges (2002) find an average daily net flow of -.02 percent of assets but an average daily magnitude (absolute value of flow) of 0.34 percent of assets.[4] This high volume of cash flow relative to the actual net cash flow suggests a greater amount of uncertainty for mutual fund managers and possible significant costs to providing the necessary level of liquidity. Edelen claims that funds lose approximately 1.4 percent per year as a result of the indirect liquidity costs to deal with this volume of share purchases and redemptions.[5]

A natural question is whether performance has a greater impact on inflows or outflows for a fund. Edelen (1999), Bergstresser and Poterba (2002), and Keswani and Stolin (2008) show a much stronger flow-performance relationship between abnormal return and inflows compared to outflows.

[4] Greene and Hodges (2002) use daily data for 211 US equity funds for the period 2/2/1998 to 3/31/2000. Their average daily absolute flow (inflow plus outflow) implies a yearly absolute flow of around 100% of assets, the approximate same order of magnitude that we find on an annual basis.

[5] Redemption fees can help control these costs. A redemption fee occurs when an investor withdraws assets from the fund shortly after purchasing shares. The introduction of redemption fees can greatly reduce flow volatility and uncertainty (Greene, Hodges, and Rakowski, 2007).

O'Neal (2004) and Cashman et al. (2007b) find similar results using performance ranks. This is consistent with investors not punishing mutual funds very much for poor performance but chasing high performance. In contrast, Ivkovic and Weisbenner (2009) find that inflows are sensitive to relative performance, but outflows are sensitive to absolute performance

The flow-performance relationship has been examined in contexts other than the U.S. mutual fund industry. Hedge fund flow is monotonic with performance, though there is disagreement as to whether it is convex (Agarwal, Daniel, and Naik, 2004), concave (Goetzmann, Ingersoll, and Ross, 2003), or linear (Baquero and Verbeek, 2009). Hedge fund lockups may generate a concave relationship as investors cannot easily enter or leave the fund and confound research on hedge fund flows (Ding, Getmansky, Liang, and Wermers, 2009). Pension fund investors punish poor performance and do not present the convex relationship seen in mutual funds (Del Guercio and Tkac, 2002). Finally, private equity funds flows are concave with performance (Kaplan and Schoar, 2005).

3. Data and preliminary analyses

3.1 Data sources

We examine actively managed, equity mutual funds over the period 1996 through 2009. To build our database, we first downloaded and parsed all available Form N-SAR filings from EDGAR (the details of this process are provided in a technical appendix). All U.S. mutual funds are required to file Form N-SAR on a semi-annual basis, and the data begin to appear consistently in EDGAR in January 1996, the start of our sample.[6] Thus, our initial dataset is the entire population of U.S. mutual funds over our sample period.

[6] A small sample of funds voluntarily filed and/or had their reporting requirements phased in prior to 1996. To mitigate selection bias, we only examine data from the period following mandatory disclosure.

The N-SAR filings allow us to extract a large number of items that are unavailable in other databases, such as monthly inflows/outflows, compensation arrangements, and investment constraints. A limited number of previous studies have used much smaller subsets of this data to examine various issues including advisory contracts (Deli, 2002; Warner and Wu, 2011), investment constraints (e.g., the ability to short sell) (Almazan, Brown, Carlson, and Chapman, 2004), and the use of performance-based compensation (Dass, Massa, and Patgiri, 2008).

The semi-annual frequency of the N-SAR filings severely limits the number of available return observations, so we merge our N-SAR data with the CRSP Survivor-Bias-Free U.S. Mutual Fund Database, which has monthly returns. We include a fund in our sample if, based on CRSP, the fund holds at least 80 percent of its assets in equity and has at least $20 million in total net assets (TNA).[7] We screen out index funds, variable annuities, ETFs, tax-managed products, REITs, and lifecycle funds. In the N-SAR filings, fund flows are only reported at the fund level, not at the share class level. So, as is commonly done, we collapse funds with multiple share classes into a single fund. We eliminate individual fund-months if the month-to-month change in TNA is greater than 200 percent or less than -50 percent; the fund is acquired or does an acquisition; or there is a clear data error (e.g., a negative inflow). In addition, we remove the first two years of a fund's performance history to mitigate incubation bias (Evans, 2010).[8]

Merging the CRSP and N-SAR databases is complicated by the fact that there is no common identifier. We begin by using a name and ticker symbol matching procedure similar to Warner and Wu (2011). For cases that have similar, but not exact, name matches, we use joint information in the two

[7] To avoid selection/survivorship bias for funds that attempt to market time or whose assets fall due to poor performance, we include a fund once it crosses the 80 percent equity/$20 million TNA threshold for the first time. Once a fund enters our sample, it remains even if it drops below the 80 percent/$20 million cut-off. In unreported analyses, we also considered a $50 million TNA threshold and found that our results are not influenced by which cutoff we use.

[8] Our sample begins in 1996, thus removing the first 24 months of returns has no impact for funds born before 1994. It also has no impact for funds that don't reach our $20 million threshold before their second anniversary. Nonetheless, this screen necessarily induces some degree of survivor bias for larger funds born after 1994.

databases (e.g., TNA and turnover) to confirm the match. All of our algorithmic matches are subsequently hand-verified for accuracy. For every CRSP fund we could not match algorithmically, we search by hand for an N-SAR match. In all, we match a total of 72,118 filings to a CRSP mutual fund, which represents, by a wide margin, the most extensive merger of the CRSP and N-SAR databases to date. We ultimately are able to map 94.5 percent of our CRSP universe to the N-SAR filings, which represents a more than 50 percent increase over the Warner and Wu (2011) sample (the next largest).[9]

We collect additional information from CRSP, including fund styles, expenses, turnover ratios, age, and monthly returns.[10] We assign funds to one of nine style categories based on stated fund strategy. Because there are multiple objective code sources in CRSP, we assign a style category based on values from the following sources, listed in terms of priority: Wiesenberger, Strategic Insight, Lipper, and Thomson Reuters. We calculate a fund's age from when it first appears in CRSP.

As a further guard against data errors and potential mismatches between CRSP and N-SAR data, we compare the N-SAR and CRSP net flows. CRSP does not report actual net flow, so we compute the implied net flow for fund *i* for period *t* as:

$$Implied\ net\ flow_{i,t} = \frac{TNA_{i,t+1} - TNA_{i,t}(1 + r_{i,t})}{TNA_{i,t}} \tag{1}$$

where $r_{i,t}$ is the fund's CRSP-reported return for the month. Because the CRSP-implied flow is an approximation, it never matches our N-SAR flow precisely. We eliminate fund-months with the most

[9] In Table I of Warner and Wu (2011), the authors document that they collect 112,614 semi-annual filings with valid contract data, and they match 42,072 filings to a valid CRSP mutual fund (37 percent hit rate). Following this logic, we collect 128,714 semi-annual contracts with valid flows data and are able to match 72,118 to CRSP (56 percent hit rate). However, their hit rate includes non-equity funds and ours does not.

[10] For funds with multiple share classes, the TNA-weighted average across all share classes is used for each fund's returns, turnover, expense ratio, and percent institutional class.

extreme differences by trimming fund-months at the 1 and 99 percent levels (based on the difference in the net flows).[11]

Finally, we require lagged filings for each fund to enable construction of our lagged independent variables (discussed in a subsequent section). Our final sample contains 732 fund families, 3,735 unique actively managed, equity funds, and 279,657 fund-month observations.

3.2 Summary statistics

Table 2 provides summary statistics on fund characteristics for our final sample at the fund level (summary statistics on fund flows appear in Table 3). As shown, the average fund in our sample has $798 million in TNA. The median is much smaller at $159 million, reflecting the considerable skewness in fund size (because we have already screened out the smallest funds, the true population means and medians are somewhat smaller). The average family TNA is $30 billion, with a median of $5 billion. Note that our "family" variable is based only on the funds in our sample. In other words, the TNA for a particular family is equal to the sum of the TNAs for family funds that appear in our sample, so we only capture family size in terms of equity funds that we match to the N-SAR database. The true family TNAs, once fixed income and other funds are included, would be much larger in many, if not most, cases. Using our definition, there are 732 families, of which 321 contain a single fund only. The average number of funds in a family is 16.1; the average number of funds, conditional on there being more than one fund in our sample, is 18.4.

[Insert Table 2 about here]

Our average (median) fund is 9.4 (6.5) years old, meaning that the average (median) fund has 9.4 (6.5) years of data in CRSP. Similar to what other studies have reported, the average fund expense

[11] The correlation of the implied CRSP flow and the actual net flow from the N-SAR filing is 99.6 percent.

ratio is 1.4 percent, and the average turnover is 101 percent (median turnover is smaller at 76 percent).[12] New share classes are introduced at one or more points in our sample by 33.5 percent of our funds; conditional on ever introducing a new class, the average number of new classes is 1.6 in total.[13] With multi-class funds, different classes typically have different types of loads. Because we necessarily collapse such funds into a single entity, we can only create a single variable indicating the presence or complete absence of loads. Thus, 56.9 percent of our funds charge a load of some type for a least one class. Further, 66.7 percent of our funds indicate in their N-SAR filings that they have short-term trading fees, and their use has grown from about 60 percent at the start of the sample to nearly 75 percent by 2009.[14] These fees are most prevalent in load funds.

The median minimum investment of $1,000 is as expected, but the average of $139,000 is surprising at first glance. The reason for the difference is that a relatively small number of institutional funds have minimum investments reaching into the tens of millions. The skewness is so great in this case that the mean is noticeably larger than the 90th percentile. The existence of these funds also explains why some funds have relatively few accounts.[15]

Over our sample period, the average fund has an average monthly return of .27 percent with a standard deviation of 5.41 percent per month. By comparison, the CRSP value-weighted index returned .20 percent per month with a standard deviation of 6.74 percent over the same period. Finally, the

[12] The expense ratio is from CRSP and is the management fee only. Loads, 12b-1, and other fees are not included. Turnover, also from CRSP, is the SEC-mandated formulation of the lesser of aggregate purchases or sales, divided by average monthly TNA.

[13] Beginning consistently in 1999, CRSP tracks when funds close to new investment. Almost 20 percent of our funds close at least once. Among funds that close, the average length of closure is 32.8 months, which represents 39 percent of the life of the fund in our sample. In unreported analysis, we include an indicator variable as to whether the fund was closed in our flow models (Table 4); the results are similar.

[14] The data for short-term trading fees come from question 37 of the N-SAR filing. We note, however, that of the 66.7 percent of funds that state that they charge short-term trading fees, only 39 percent of the funds actually collect any fees from the program (question 38). As a robustness check, we form our indicator variable for short-term trading fees based on whether the fund actually collected any fees under the program. Our results are not affected by which question we follow.

[15] For example, in 2006, the GMO U.S. Growth Fund had a minimum investment of $10,000,000. This fund is coded as "institutional" in CRSP and had only 34 shareholder accounts.

average (median) fund had a four-factor Carhart (1997) alpha of -.10 (-.08) percent per month (calculated over the trailing 12 months of returns).

Table 3 provides summary statistics on monthly flows at the fund level. As shown, the average and median monthly net fund flow (as a percentage of beginning-of-month TNA) are .05 and .02 percent, respectively, but there is considerable variation. At the 10th and 90th percentiles, average net flows are -2.30 and 2.95 percent per month. The standard deviation of the average net flow is 4.13 percent per month.

[Table 3 about here]

The fact that the average fund has a monthly net flow of essentially zero tends to mask the fact that inflows and outflows, while often similar in size, can be quite large. As shown in the table, the average fund experiences monthly inflows (outflows) of 4.67 (4.62) percent of beginning-of-month TNA.[16] To put these numbers in perspective, the corresponding annual figures are inflows of 61 percent and outflows of 50 percent (both as a percentage of beginning-of-year TNA). At the 90th percentile, annual inflows and outflows are 137 and 94 percent, respectively.

Overall, a total of 26,832 fund-months (9.6 percent of our sample fund-months) have inflows of greater than 10 percent of beginning-of-month assets. Similarly, 20,683 fund-months (7.4 percent of our sample) have outflows of greater than 10 percent of beginning-of-month assets. Individual funds are, at times, hit with enormous flows. For example, in January of 2005, the Rydex Precious Metals fund received inflows equal to 60.3 percent of its beginning-of-month TNA, while at the same time experiencing outflows of 58 percent. The net flow for the month is a modest 2.3 percent, again illustrating how focusing on net flows can obscure the level of underlying activity. Over the eight-year

[16] Throughout this paper, "inflows" refers to inflows that are not reinvestments of distributions. Thus, the inflows are "new" money. Section 3.3 discusses this issue in more depth.

life of the Rydex Precious Metals fund (in our sample), the average monthly inflow is 46.7 percent of beginning-of-month TNA, while the average monthly outflow is 51.2 percent.

Extraordinary flows are not limited to small and/or specialized funds. For example, The Putnam Investors Fund, which Morningstar classifies as a large-cap blend fund, managed over $1.6 billion in assets at the beginning of December of 2008. During the month, the fund received inflows of $321.5 million and outflows of $368 million. These flows accounted for 20 and 22.9 percent of the fund's beginning-of-month assets, respectively, but the net flow was only -2.9 percent. In section 4.4, we explore how such large flow shocks affect subsequent fund performance.

Table 3 also shows average flow volatilities and correlations. For the average fund, net flows have a standard deviation of 5.22 percent per month, which is greater than volatility of either inflows (4.43 percent per month) or outflows (4.14 percent per month). The greater volatility for net flows is a reflection of the fact that inflows and outflows are not highly correlated; on average, for the typical fund, the correlation is only .20, with a median of .12. Further, these correlations may be overstated. Because our monthly flows are aggregated from daily flows, inflows and outflows are probably made to look more synchronous than they really are.[17] Also, and not surprisingly, inflows and net flows are positively related; the opposite is true for outflows and net flows.

Finally, for perspective, the last two rows in Table 3 provide aggregate flows (in our sample). As shown, aggregate monthly inflows (outflows) average about $52 ($49) billion. The single largest monthly inflow occurred when investors, with exquisite timing, poured in $873 billion in March of 2000. The single largest outflow occurred in October 2008, when the market lost nearly 20 percent of its value.

[17] To further illustrate the impact of aggregation, the annual inflows and outflows are more highly correlated, with a mean (median) correlation of 0.32 (0.38).

3.3 *Flow seasonality*

As shown in Figure 1, aggregate mutual fund flows exhibit seasonality. The largest inflows of new capital occur at the beginning and end of the year; the average inflow of new capital for the months of January and December is 13 percent larger than the average for the rest of the year. Outflows are 17 percent higher in December compared to the rest of the year. These differences are highly significant economically and statistically.[18] As a result, we control for month of the year in subsequent multivariate analyses.

[Figure 1 about here]

The N-SAR filings break out fund flows into new sales, redemptions, and the reinvestment of dividends and distributions. Figure 1 shows a strong end of the year effect for the reinvested flows, which is a reflection of the fact that funds tend to declare distributions in the fourth quarter. The average inflow of reinvested capital for the month of December is 3.68 percent of the fund's beginning of period assets. For comparison, the average inflow of reinvested capital for the rest of the year combined is only 1.04 percent.

Throughout this paper, we ignore inflows that come from reinvestment of distributions. The reason is that our focus is on how investors respond to performance. In unreported analyses, we have studied the behavior of reinvested flows, and we find little sensitivity to returns, risk, or other variables in our model (other than a very strong December fixed effect).

[18] We reject the hypothesis that inflows for the months of January and December are equal to the inflows for the remainder of the year (t = 19.4) and reject the hypothesis that outflows for the month of December are equal to outflows for the remainder of the year (t = 14.4).

4. Fund flows and prior performance

In this section, we examine the relation between fund inflows, outflows, and net flows and prior performance. We have two main goals. First, we want to compare the relative sensitivity of inflows and outflows with respect to a variety of both standard and new controls. Our second goal is to determine whether investors care about raw returns, risk, or both, and also whether inflows and outflows react similarly to performance.

4.1 Baseline regression results

We examine flow/performance relations on a monthly basis using panel regressions covering the January 1996-December 2009 period. Our baseline models take the general form:

$$Flow_{i,t} = Return_{i,t-1} + Risk_{i,t-1} + Controls_{i,t-1} + Fixed\ effects_{i,t} + \varepsilon_{i,t} \qquad (2)$$

In eq. (2), the dependent variable is, for each fund *i* and month *t*, either the inflow, outflow, or net flow expressed as a percentage of beginning-of-month TNA. Inflows and outflows only take on positive values.

Our controls consist of variables widely used in previous research, along with some that are new to the literature because of their availability in the N-SAR data. Six of our controls are continuous:

1. *Log age*, log of age (as of the beginning of the month, CRSP),
2. *Log size*, log of TNA (as of the beginning of the month, CRSP)
3. *Log family size*, log of fund family TNA (as of the beginning of the month, CRSP),
4. *Log # accts*, log of the number of accounts (as of the end of the most recent N-SAR),
5. *Turnover ratio*, turnover (as of the end of the most recent fiscal year, CRSP), and
6. *Expense ratio*, expense ratio (as of the end of the most recent fiscal year, CRSP).

The last three of these variables only change value for a particular fund either every six months or twelve months, depending on source.

We also have three dummy variables:

1. *Load fund*, equal to one if the fund has a front- and/or back-end load (N-SAR),
2. *Short-term fee*, equal to one if the fund has a short-term trading fee (N-SAR),
3. *New share class*, equal to one if the fund introduces a new share class in the month (CRSP).

Finally, our primary interest is the impact of prior performance on flows, so we include both the raw return (*Raw return*) and the standard deviation of the raw return (σ) from the previous twelve months.[19,20] In effect, we include both the numerator and the denominator of the widely used Sharpe ratio to assess the relative importance of each. Also, many previous studies (e.g., Sirri and Tufano (1998)) find a convex relation between flows and performance, so we include the squared return as well.[21] Our regressions include fund, month-of-the-year, year, and style fixed effects.[22,23] We cluster the residuals by fund and use robust (to heteroskedasticity) standard errors. We lose observations for each fund because of variables that require lagged N-SAR data (e.g., the number of accounts). The estimates appear in Table 4.

[Insert Table 4 about here]

To ease interpretation of the results, we convert all continuous independent variables (but not the dependent variable) to *z*-scores (the values are de-meaned and then divided by their standard

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[19] It is not obvious over what time frame investors evaluate mutual fund performance, though the tournament and persistence literatures typically assume an entire year. We test both longer and shorter time periods and our basic results are unaffected.

[20] In unreported analyses, we experimented with including trailing 12-month and 36-month Carhart (1997) four-factor alphas instead of volatility. The coefficient on lagged return is economically and statistically larger than the coefficient on alpha, similar to our subsequent analysis of standard deviation of returns. Because alphas and raw returns are positively correlated, particularly for very high or very low returns, we focus on a simpler metric of risk: standard deviation.

[21] Kim (2010) presents evidence that the convexity of the flow/performance has diminished or disappeared in more recent years. Cashman, et al. (2008) document that outflows are also convex in performance. For robustness, we also tested cubic and piece-wise linear specifications of the flow performance relationship, the results are similar.

[22] We also considered a less parsimonious specification using individual month fixed effects rather than year and month-of-the-year fixed effects; our results are essentially the same.

[23] Because of the fund fixed effects, we are able to identify several of our variables only because of funds that make a change. For example, most funds are either load or no-load for their entire life in our sample, but a small number convert, allowing us to estimate the coefficient on the load dummy.

deviations).[24] The effect of doing so is that an estimated coefficient measures the impact on the dependent variable of a one standard deviation move in the independent variable, thereby allowing a direct comparison of the economic significance of the variables in the model.[25]

The first model in Table 4 examines net flows. Most of the control variables are highly significant statistically with the expected signs. The notable exceptions are the expense ratio, which has essentially zero impact, and family size, which has only a marginal impact on net flows.[26] Turnover has a negative coefficient, but it is not significant at the one percent level. The most important control from an economic standpoint is, by a wide margin, fund age. A one standard deviation increase in log age decreases net flows by almost three percent, which is quite large relative to the typical fund's monthly net flow.

Trailing 12-month raw returns have a large impact on net flows. A one standard deviation increase in returns (1.32 percent) increases net flows by 1.39 percent, and the coefficient is significant at any conventional level. The coefficient on squared returns is negative and highly significant statistically, suggesting a concave relation. However, the coefficient is relatively small economically, suggesting that any deviation from linearity is not large. Finally, the coefficient on trailing volatility is economically and statistically zero. Taken at face value, these results suggest that, on a net basis, net flows chase raw returns, disregarding risk in the process.

Volatility measures have been included in previous fund flow studies (usually as a control rather than a variable of interest). These measures typically have negative coefficients but are not necessarily highly significant. Sirri and Tufano (1998), for example, find a marginally significant

[24] The de-meaning has no impact on the slope coefficients; it just converts the intercept to a "center-cept."

[25] We also considered including the lagged dependent variable in our panel (e.g., Cashman et al., 2007a) to address the persistence in flows; its inclusion has no meaningful impact on the conclusions of our model. Further, inclusion leads to dynamic panel bias because, with our fixed effects, the lagged dependent variable is necessarily correlated with the residual. See, e.g., Flannery and Hankins (2010) for a discussion of dynamic panel bias in finance applications.

[26] When we collapse multiclass funds, the expense ratio is a weighted average across classes and is thus noisy. However, when we estimate eq. (2) on single family funds only, expense ratios continue to have little economic impact on flows.

negative coefficient in some specifications, but no significance in some alternatives. However, an insignificant coefficient on volatility in net flow regressions doesn't necessarily mean that investors are indifferent to volatility; rather, it really only tells us that inflows and outflows are similarly affected (we explore this question directly in subsequent analyses). Previous studies also suggest that, due to a convex flow/performance relation, funds may have an incentive to increase return volatility, but our estimates indicate that volatility has no impact on net flows.

Importantly, the coefficients for the net flows in model 1 are exactly equal to the difference between the inflow and outflow coefficients in models 2 and 3, and the *t*-statistics in model 1 test for differences between those coefficients. Thus, the fact that most of the coefficients in model 1 are highly significant immediately tells us that the associated variables have differential impacts on inflows and outflows.

Turning to the inflows in model 2, most of the coefficients are, broadly speaking, similar to what we observe for net flows in model 1. However, squared returns have no impact on inflows, suggesting a linear inflow/performance relation. Turnover and short-term trading fees are both significant for inflows with the opposite signs (compared to net flows). A look at the corresponding outflows in model 3 explains what is happening. Short-term trading fees deter inflows, but have a greater impact on outflows, so the overall effect on net flows is positive. Similarly, turnover has a small positive impact on inflows, but a much larger positive effect on outflows, so the net effect is negative.

Also, family size is highly significant for inflows, but it also highly significant for outflows (with a comparably sized coefficient), which explains why the difference is not highly significant in model 1. We interpret these results as large families generating more activity for member funds, though not necessarily more net flow. Family size is a good example of how looking at the disaggregated flows can paint a richer picture of flow activity than net flows.

As with net flows, inflows chase previous raw returns, but ignore volatility. The return chasing is somewhat smaller economically for inflows than for net flows. The reason is that outflows flee past returns (meaning that a decrease in raw return leads to an increase in outflows).

Comparing inflows and outflows along other dimensions reveals some additional differences. Introducing a new share class has a large effect on inflows, but doing so also increases outflows. Older funds have lower inflows and higher outflows. Fund size has a large negative effect on inflows and a smaller negative effect on outflows. Loads are significant for inflows, but not for outflows.

4.2 Do all investors chase returns?

It is often supposed that institutional investors are more sophisticated than "retail" investors (e.g., Stein (2009)). We therefore explore whether these two types of investors behave differently in the context of our panel model in Table 4. Based on CRSP, about 73 percent of the mutual funds in our sample are either entirely institutional or entirely retail, which provides us with an interesting natural experiment. Using only this subset of funds, we create a dummy variable, *Institution*, which takes on a value of one for the institutional funds. We include this dummy in our panel model and also interact it with every independent variable in the model. The results are reported in Table 5.

[Table 5 about here]

For presentation purposes, for each flow type (net, inflow, and outflow), we present the coefficients on the variables in the first column and the coefficients on the institutional dummy and the interactions in the second column. Thus, the coefficients in the first column represent the estimates for the retail investors; the estimates in the second column are the shifts in the coefficients for the institutional investors. A significant coefficient in the second column means that the institutional flows have a different sensitivity to the variable in question. As in our previous analyses, all of the continuous independent variables are *z*-scored. The coefficients for the net flows (and the shifts) are exactly the difference between the corresponding inflow and outflow coefficients, and the *t*-statistics for net flows test whether the corresponding inflow and outflow coefficients differ.

Beginning with the net flows, the only control that is dramatically different for institutions is age, which has a stronger negative impact on institutional flows. The institutional dummy variable is not significant, but, more importantly, we see that institutional net flows chase returns to a significantly smaller degree than retail net flows. The squared return has no impact for either retail or institutional flows.

Further, retail investors chase volatility. The coefficient on lagged standard deviation of returns is positive and statistically significant, though of modest size economically. For institutional investors, the coefficient on volatility is negative and statistically significant. However, the coefficient on this interaction term is simply a measure of whether institutions behave differently than retail investors (the coefficient on the main effect), which they do. To address risk on the flow of institutional capital, we have to add these two coefficients together, which yields a statistically insignificant coefficient of -.19 (=.22 - .41).

For inflows, among the controls, fund size has a more negative impact on institutional inflows, and the short-term trading fee has less of an impact. The institutional dummy is not significant. The return chasing by retail inflows is similar to what we observe for net flows, but the volatility chasing is more pronounced. The institutional inflows chase returns to a much smaller (though still highly significant) degree, and the coefficient on volatility is negative and statistically significant, but economically small at -.0017 (=.0038 - .0055). The squared return is large and highly significant for retail investors, but very small (.0056 - .0048 = .0008) and statistically insignificant for institutional investors. Thus, there is evidence of a convex inflow/performance relation for retail investors, but not for institutional investors.

Finally, for outflows, age has a much stronger impact on institutional outflows, meaning that older funds experience larger outflows. Both types of investors chase returns to essentially the same degree. Retail investors avoid volatility, meaning that greater volatility increases outflows, but the coefficient is small and not highly significant. Volatility has essentially no impact on institutional outflows. The squared return is large and highly significant for retail outflows, but much smaller (.0060 - .0048 = .0012) and not statistically significant. Over the relevant range of returns, the coefficients for return and squared return imply a downward sloping, convex relation for retail outflows (i.e., the first derivative is negative for monthly returns smaller than 34 percent)

Overall, the results in Table 5 provide relatively clear evidence that institutional inflows and net flows chase returns to a smaller, but still significant degree. Further, unlike the retail flows, the institutional inflows and net flows don't chase volatility. These results might suggest that institutional investors are more sophisticated in some sense, but the fact that institutional outflows don't avoid volatility to the same degree as retail outflows clouds this interpretation.

For retail investors, we also find a relatively strong convex return relation for both inflows and outflows (with opposite signs on returns). Both relations are much more linear for institutional investors. Because the squared return has a similar impact on retail inflows and outflows, net retail flows behave linearly. Once again, looking at the disaggregated flows provides significant additional insight.

4.3 Panel quantile regression analyses

In our panel models thus far, we have explored flows under the usual least squares assumptions. In particular, we have assumed that the impact from the independent variables is constant over the entire flow distribution. This assumption is always questionable. With our data for instance, it is reasonable to wonder if high flow funds differ from low flow funds. To address this question, we turn to a panel quantile regression framework (Koenker and Bassett (1978)) to evaluate the effect of return chasing over the range of quantiles of the flow distributions.[27]

The most common application of a quantile regression is a median regression in which the sum of the absolute errors is minimized to estimate a median effect on the response variable. However, the same framework can be used to estimate the effect on any quantile in the distribution and proves particularly useful in evaluating the impact of an independent variable, in our case returns and volatility, at different points of the flow distribution (e.g., are inflows as sensitive to returns at the 10th quantile as they are at the 90th quantile?). Additionally, the semi-parametric nature of quantile regression mitigates the effect of outliers in the data.

The panel nature of our data, however, creates a problem with quantile regression because of the fund fixed effect. In principle, fixed effects can be handled in a quantile regression through the use of dummy variables, which is what we do for our month, style, and year fixed effects. However, adding a dummy variable for each fund in our data (3,699 funds) renders our model computationally infeasible. Further, simply de-meaning the fund "fixed effect" from the data is not appropriate because, unlike expectations, conditional quantiles are not linear operators.

Because of this issue, we estimate models using an approach suggested in Canay (2010). Specifically, we estimate eq. (2) from above and capture the estimated fixed effect for each fund. We

[27] Koenker and Hallock (2001) provide a very readable overview of quantile regression.

then transform the dependent variable(s) in our model(s) by subtracting the fund fixed effect. Canay shows that this two-step estimator is consistent and asymptotically normal as *n* and *T* go to infinity. In finite sample simulations (involving in some cases panels much smaller than ours), the bias of the two-step approach is quite small; however, Canay only considers balanced panels.[28]

We obtain coefficient estimates for net flows, inflows, and outflows for the 5th through 95th quantiles in five percent increments. As before, we use *z*-scored continuous independent variables, but, strictly speaking, the coefficients no longer measure the impact of a one standard deviation move because the conditional quantile variances need not be equal. Because the amount of output that is generated is considerable, we summarize the results of these analyses graphically in Figure 2. We obtain standard errors via the bootstrap approach with 500 repetitions. Each graph shows a plot of a coefficient along with a 95 percent confidence interval. In several cases (e.g., age), the standard errors are extremely small, so the confidence intervals are not easily distinguished from the plot. For the sake of brevity, we only discuss selected covariates.

[Figure 2 about here]

If the OLS assumption of a constant coefficient across the quantiles were correct, the plots would be horizontal lines. For example, in the net flow model of Table 4, the estimated effect of family size on net flows was a moderately significant 0.0021 (*p*-value = .095). From Panel A of Figure 2, we see that the effect is not constant throughout the flow distribution. Rather, when flows are large, funds have a greater (positive) sensitivity to family size, but this effect diminishes for lower flow funds, eventually becoming negative for funds that fall below the 10th quantile of net flows.

[28] The procedure from Canay (2010) relies on the fact that the fixed effect is a constant shift variable over the entire distribution of flows. To test how this assumption impacts the results of our models, in informal analyses, we experimented by repeatedly drawing 250 funds from our panel at random and then estimating the quantile panel using dummy variables for the funds (250 was the largest number of funds we were able to run at one time). We then compared the performance of the “dummy” variable and Canay (2010) approaches. We found that the estimated coefficients between the two approaches were similar and thus did not materially impact any conclusions.

We observe similar variation across the quantiles for essentially every coefficient in Panel A of Figure 2. Several have opposite signs for high and low net flow quantiles. Focusing on some of the most economically significant controls, age is much more important for high net flow funds. Fund size has a positive impact on low net flow funds and a negative impact on high net flow funds; the reverse is true for family size and loads. Prior return has a relatively constant impact up until the 60th quantile, at which point the coefficients begin to increase sharply. The coefficient at the 90th percentile is about three times the coefficient at the median. The impact of the squared return is interesting because it changes sign, indicating concavity for low returns. The coefficient tends to get progressively larger as we move toward 90th percentile, suggesting that the convexity for net flows is increasingly more pronounced for large flow funds. Lagged volatility also changes sign, and it becomes positive and highly significant for the highest net flow quantiles.

As with net flows, the coefficients for inflows in Panel B of Figure 2 vary across the quantiles. The coefficients are always larger (absolute value) for the high inflow quantiles, indicating that high inflow funds differ from low inflow funds in many dimensions. Surprisingly, for example, high inflow funds have large and highly significant positive coefficients on turnover and expense ratios. The coefficient on lagged return increases steadily as we move from low to high inflow quantiles. The squared lagged return behaves similarly. The impact of lagged volatility grows slowly up until the 80th quantile, at which point it climbs steeply.

Finally, the coefficients for outflows in Panel C of Figure 2 clearly show that high outflow funds have greater sensitivities to variables in the model than low outflow funds. Most of the variables in the model have relatively small impacts on low outflow funds. Variables such as age, size, short-term trading fee, and turnover have a modest impact below the median and begin to change much more noticeably above it. Lagged returns become steadily more important as do squared returns, again suggesting an increasingly convex relation. Volatility also becomes progressively more important.

It seems odd a first glance that both high inflow and high outflow funds are more sensitive to volatility. However, funds with very large and very small returns tend to have particularly high volatility, so the effect may be a by-product of return chasing. To illustrate, we sorted all of our trailing twelve month returns into deciles and calculated the average associated trailing standard deviations. The result is displayed in Figure 3. As shown, there is a relatively clear relation between trailing volatility and return. The fund-months in the lowest and highest return decile have much greater volatility than those in middle deciles. Thus, investors who chase returns, good and bad, may simply be mechanically chasing volatility.

[Figure 3 about here]

Taken together, our quantile panels tell a consistent story; namely, high flow funds are different from low flow funds. Variables in the model generally have much larger impacts on high flow funds. Consequently, focusing on the average effect (as in our baseline panel in Table 4) obscures the influence of many (if not most) of the variables in the model. The coefficients on return, for example, are two to three times larger at the 90^{th} percentile than they are in our baseline panel.

4.4 Is return chasing hazardous to fund investors' wealth?

Our results thus far show that investors chase past performance as measured by raw returns, and they appear to do so without regard to risk. In this subsection, we ask whether this behavior is harmful. Specifically, we compare the performance of flow-weighted returns ("new" money) to TNA-weighted returns ("old" money) to examine whether investors' flow decisions are "smart." The issue of whether mutual fund investor flows are smart was first explored by Gruber (1996) and later in such studies as Zheng (1999), Sapp and Tiwari (2004), Friesen and Sapp (2007), and Keswani and Stolin (2008). The general conclusions reached in this line of literature are mixed and depend on time period, factor pricing model, and locale.[29]

In the paper most closely related to ours, Keswani and Stolin (2008) study monthly inflows and outflows for UK funds over the period 1992 – 2000. Their primary conclusion is that inflows (but not outflows) are smart. Further, only retail investors (as opposed to institutional investors) are smart. Because these results are quite puzzling, we examine the issue using similar methods with our much larger and more recent US sample.[30]

Using inflows as an example for concreteness, for each month t, we compute the inflow weight for each fund i as the fund's inflow for the month divided by aggregate inflows for the month (which is, in effect, the fund's inflow market share for the month). We then use these weights to calculate a portfolio return in month $t + 1$. Similarly, we compute *TNA* weights in month t and a portfolio return in month $t + 1$. The *TNA* values used at t are calculated as $TNA_{t-1}(1+r_{i,t})$, where $r_{i,t}$ is the fund's return for the month. This calculation provides the "would-have-been" *TNA*, i.e., the end-of-month *TNA* that would have existed had there been no flows.[31]

This process produces two time-series of monthly portfolio returns. We take a long position in the new money portfolio and a short position in the old money portfolio and regress this difference on

[29] Gruber (1996) and Zheng (1999) find that portfolios formed on investors flows appear to outperform, while Sapp and Tiwari (2004) find that, after controlling for momentum, flows have no predictive ability. Friesen and Sapp (2007) do a more specific test of the returns to cash flows and find that dollar-weighted returns have persistent losses. Keswani and Stolin (2008), however, show that for a sample of UK mutual funds, even after controlling for momentum, "smartness" exists and that the U.S. results in Sapp and Tiwari are time-varying.

[30] In an average year, Keswani and Stolin (2008) have 311 funds with flow data; the average fund size is £140 million (or roughly $250 million). In our sample, the corresponding numbers are 3,735 funds with an average size of $798 million. Their timeframe extends from 1992-2000 while ours runs from 1996-2009.

[31] This interpretation implicitly assumes that a fund's performance is not significantly affected by its flows, an issue we discuss subsequently. Further, it implicitly assumes all flows occur at the end of the month when they actually happen throughout the month.

the three Fama-French (1993) factors along with Carhart's (1997) momentum factor.[32] The alpha from this four-factor model is our measure of smartness. We do the same test for outflows. A positive alpha for inflows indicates smartness; the opposite is true for outflows (a negative alpha in these cases indicates that investors avoided poor performance). The results are reported in Table 6.

[Table 6 about here]

In Panel A of Table 6, we examine portfolios weighted by inflows, outflows, and net flows for our overall sample and separately for our retail and institutional subsamples. In contrast to Keswani and Stolin, we see no evidence that inflows are smart overall and there is no significant difference between retail and institutional inflows. However, and also in contrast to Keswani and Stolin, outflows appear at least somewhat smart for our overall sample, though not for the retail and institutional subsamples.[33] For the overall sample, both the outflow- and *TNA*-weighted portfolios have economically and statistically significant negative alphas; however, the outflow-weighted portfolio's is smaller (-.20 percent per month versus -.13 percent per month). The difference between the abnormal returns for the two portfolios is a modest, but meaningful, .07 percent per month, which is significantly different from zero at the five percent, but not one percent, level. The only other noticeable difference in performance is that old money for institutional investors significantly outperforms old money for retail investors.

A potential problem with the analyses in Panel A is the comingling of a possible size effect with our performance results. Skewness in fund size ensures that the *TNA*-weighted returns are dominated by larger funds. The same cannot be said for the flow-weighted portfolios. While larger funds do receive greater dollar flows on average, percentage flows tend to be smaller when compared to small

[32] Of course, mutual funds cannot be shorted. The "shorting" we do actually just creates a benchmark-adjusted return.
[33] As described in section 4.2, our definition of institutional/retail funds excludes those funds that are a blend of retail and institutional capital. These excluded funds constitute 27 percent of our sample.

funds. As a result, large (small) funds generally have negative (positive) weights in our long-short portfolios, and we therefore confound our performance results with a test of whether small funds outperform large funds. To control for the impact of fund size on our findings, Panel B replicates Panel A after dividing funds into size quintiles each month based on *TNA*.[34] In this analysis, funds are benchmarked only against funds in the same size quintile.

Looking at Panel B, size does appear to play an important role. As in Panel A, inflows are not smart. For outflows, there is a relatively clear pattern of increasing smartness as we move from the largest quintile to the smallest. For the largest funds, outflows underperform old money by an insignificant -.04 percent. For the smallest funds, however, this alpha is economically large and highly significant at -.21 percent. These results tells us that small fund investors appear very smart with their sell orders (though not with their buys), and large fund investors are not smart with either buys or sells. However, Panel B also shows that portfolios of the smallest funds consistently have much smaller alphas than portfolios of the largest funds. Thus, for example, investors in the smallest funds appear to be smart with their outflows, but their *TNA*-weighted abnormal returns are quite poor at -.26 percent per month.

Panel C provides some economic perspective on all of this by reporting the average month raw returns (equal- and *TNA*-weighted), the average aggregate monthly *TNA*, and the average aggregate monthly inflows and outflows for the size quintiles. As shown, the largest funds had much larger returns relative to the smallest over our study period. For the largest fund quintile, aggregate *TNA* is almost five times as large as the other four quintiles, combined. Aggregate inflows and outflows are about three times as large. In the smallest quintile, where investors appear exceptionally adept at

[34] Our four-factor model includes *SMB*, which is intended to pick up a fund's exposure to the small cap stocks. Note, however, that exposure to the small cap effect is not the same thing as fund size. While it is true that small cap funds tend to be smaller, our sample also includes many small funds that focus on strategies other than small cap.

avoiding poor performance, the average monthly outflow is $442 million compared to $31 billion for the largest funds. Thus, most of the money that flows out of funds displays no particular smartness.

Taken at face value, the results in Table 6 indicate that only smaller fund outflows are smart, but the economic significance of the outflow smartness is debatable, and the concentration of the effect in smaller funds suggests an alternative as to the root cause. Smaller funds have the most volatile returns and flows. When a fund is hit with a large dollar inflow, it is probably because of strong performance in a strong market. Deploying a large net inflow is not terribly difficult; fund managers tend to simply buy more of what they like (Coval and Stafford, 2007). Any extra transactions costs will tend to be offset by positive price pressure, particularly if funds herd into similar stocks as they are known to do (Falkenstein, 1996; Wermers, 1999). Large net outflows are not so easily dealt with; fund managers may be forced into "fire sale" liquidations that generate negative short term performance (Coval and Stafford, 2007).

Under this explanation, investors don't avoid poor performance; rather, they cause it to the detriment of other shareholders in the fund. A formal test of this conjecture is beyond the scope of this paper. However, reasoning very similar to ours appears to lie behind the growing use of short-term trading and/or redemption fees. Vanguard (2010), for example, states that:

> Vanguard European and Pacific Stock Index Funds charge a 2% redemption fee on shares redeemed before they have been held for two months. Unlike a sales charge or a load paid to a broker or a fund management company, purchase and redemption fees are paid directly to the Fund to offset the costs of buying and selling securities. The 2% redemption fee is designed to ensure that short-term investors pay their share of the Fund's transaction costs and that long-term investors do not subsidize the activities of short-term traders.

Overall, our results in this section show that investors don't help themselves with their buys, but neither do they damage their wealth. Similarly, most of the sales, measured in dollars, neither create nor destroy value. For the smallest funds, sales either benefit investors or (and more likely in our view) impose costs on non-selling investors.

5. Implications of return chasing for fund managers

Fund managers face strong incentives to increase assets under management. Over 90 percent of equity fund advisory contracts stipulate fees proportional to *TNA* (Warner and Wu, 2011). Our results show fund flows respond strongly to raw performance, while risk is essentially irrelevant. The implication is clear. Imagine that a fund manager is considering two stocks, one which he expects to gain 10 percent versus a required return of 8 percent (i.e., an alpha of 2 percent) and another which he expects to gain 16 percent with a required return of 18 percent (i.e., an alpha of -2 percent). Given the incentives he faces, the fund manager should choose the higher raw return stock despite its negative alpha.

Textbook theory suggests that the manager should purchase the high alpha stock and then use leverage to obtain any desired market exposure; however, the use of leverage by mutual funds is miniscule. By the end of our sample period, 26 percent of our funds can, by charter, use leverage, but only 20 percent of these funds do. Alternatively, fund managers could provide alpha to fund investors who could, in principle, use "homemade" leverage. We have no direct evidence on the use of leverage by fund investors, but we suspect the practice is uncommon.

The incentives faced by fund managers and their need to cater to return-chasing investors may help explain why funds overwhelmingly focus on growth in their stated objectives. Almost 60 percent of the funds in our sample have objectives of aggressive growth (16 percent), growth (29 percent), or growth and income (13 percent). The search for raw returns may also be at least one of the reasons turnover is so high at many funds, and it may lead managers to focus on event-driven investing (e.g., earning surprises) as they seek out the proverbial "four bagger" (or even "ten bagger") stocks.

Two additional reasons fund managers are incented to produce raw return are simple but not much discussed in the literature. First, raw returns increase assets under management. Given that average percentage net flows in our sample are close to zero, there is much more growth in assets under management for a typical fund from raw returns than from net flows. Second, managers are benchmarked, either formally or informally, against raw return indexes such as the S&P 500, and they are also benchmarked against each other on a raw return basis. Top performing funds are routinely reported in the financial press, ranked by raw performance over some previous time period.

Raw return chasing by fund managers has interesting implications for academic and practitioner research. A line of papers beginning with Jensen (1968) and running through Carhart (1997) and Fama and French (2010) generally finds that fund managers are unable to produce positive abnormal net returns. This result is often interpreted as implying either that managers lack skill or markets are efficient, or both. But these papers all beg the question by assuming that fund managers seek to produce alpha in the first place, when, as we show, there is good reason to believe that they do not, at least not as a primary objective.

Several studies have in fact shown skill in managers' ability to earn high gross returns. For example, mutual fund buys outperform their sells in gross returns (Chen, Jegadeesh, and Wermers, 2000). Mutual fund trades greatly improve total fund return by correctly anticipating earnings announcements (Baker, Litov, Wachter, and Wurgler, 2007). Finally, a mutual fund's highest weighted stocks outperform the rest of the portfolio by 46 to 107 bps per month in gross returns (Cohen, Polk, and Silli, 2009). These studies demonstrate superior raw performance from mutual fund trades and support the idea of manager skill in earning high gross returns, but more research is needed on this important question.

6. Conclusions

The phrase "past performance is not indicative of future results" is ubiquitous in the finance industry, but equity mutual fund investors don't believe it. Instead, they chase past raw returns to an extraordinary degree. Because of the way fund managers are compensated, their incentive is to take whatever action leads to the greatest possible growth in assets under management. Our evidence shows that higher raw return leads to greater fund flows, while riskiness does not affect investors' decisions. Further, net flows to funds in our sample are typically close to zero on average, so most of the growth in assets under management comes from the raw returns generated by the fund manager, thereby providing a second strong incentive to pursue maximum returns.

Contrary to some recent research, we don't find that fund flows are "smart." For inflows, we find no evidence that investors correctly anticipate future returns. This is true for both retail and institutional investors. We find some evidence of smartness in outflows, but it occurs almost entirely in small funds. We conjecture that the "smart outflow" effect is actually caused (as opposed to anticipated) by the outflows.

Finally, many studies examine whether fund managers can generate significant risk-adjusted returns, and most conclude they do not, at least in general. This finding is often cited as evidence that fund managers lack skill. But our results suggest that this interpretation begs the question. Skilled fund managers are those who grow assets under management, not necessarily those who produce alpha. To date, however, whether this aspect of fund manager skill exists and/or persists is unexplored territory.

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Table 1: Summary of performance measures to predict mutual fund cash flow

This table summarizes the variety of performance measures used to predict cash flow in the prior literature. *Net return* means that the prior period return based on changes in NAV was used. *Market-adjusted return* is the net return less the return on the market (however defined). *Alpha* indicates the use of a Jensen alpha and may include any risk model. *Net return rank* and *Risk-adjusted rank* indicates the use of the relative rank of the fund's net return and risk-adjusted return, respectively, and typically varies from 0 to 1. *Residuals* means the error terms from a factor model were used. A *Spline* or *Kinks* includes a change in the slope at some predefined point. *Polynomial* includes the square or higher order polynomial of the performance measure to capture asymmetric reaction to returns. *Multiple lags* uses performance measures from multiple prior periods. This list of studies is representative, not exhaustive.

		Performance measure								
Authors	**Year**	**Net return**	**Market-adjusted return**	**Alpha**	**Net return rank**	**Risk-adjusted rank**	**Residuals**	**Spline or Kinks**	**Polynomial**	**Multiple lags**
Ippolito	1992						x	x		x
Chevalier and Ellison	1997		x							x
Sirri and Tufano	1998				x					
Khorana	2001			x						
Bergstresser and Poterba	2002	x								
Del Guercio and Tkac	2002		x	x				x		
Karceski	2002		x							
Elton, Gruber, and Blake	2003				x					
Lynch and Musto	2003			x				x		
Nanda, Wang, and Zheng	2004			x						
O'Neal	2004			x		x				x
Barber, Odean, and Zheng	2005		x						x	
Berk and Tonks	2007	x		x	x				x	
Cashman, Deli, Nardari, and Villupuram	2007a					x				
Cashman, Deli, Nardari, and Villupuram	2007b			x						x
Coval and Stafford	2007	x								x
Huang, Wei, and Yan	2007					x				
Del Guercio and Tkac	2008	x								
Keswani and Stolin	2008			x						
Gil-Bazo and Ruiz-Verdu	2009			x						
Ivkovic and Weisbenner	2009	x			x					
Kim	2009		x			x			x	x
Sensoy	2009		x	x				x		
Singal and Xu	2009				x					
Spiegel and Zhang	2009		x			x		x		
Evans	2010				x	x				
Reuter and Zizewitz	2010			x						x
Yadav	2010				x					

Table 2
Summary statistics by fund

Table 2 provides summary statistics for the sample of active, equity fund managers used in this study. The time period of study covers January 1996-December 2009. The unit of observation is an individual fund; we aggregate (TNA-weighted) multiple share classes to form one fund observation. We define *Family TNA* and *Fund TNA* as the total amount of money managed by the family/fund (in millions), *Age* is the length of time (in years) that the fund was in CRSP. *Expense* and *Turnover ratio*, and the introduction of a *new share class* (indicator variable) are from CRSP, the presence of *Loads* and *Short-term trading fees* are indicator variables from the N-SAR data indicating the presence of such fees. *Number of Accounts*, *Minimum Investment*, and *Average account size* are from N-SAR. *Institutional TNA* is the percentage of the fund's TNA that is coded as institutional in CRSP. Our performance measures are the fund's monthly *return*, monthly *standard deviation* of returns (estimated over the preceding 12 months), and the intercept *(Jensen's alpha)* from a 12-month regression of the funds' return on the Carhart (1997) 4-factor model.

Variable	N	Mean	Median	10%	90%	Standard Deviation
Fund TNA ($MM)	3,735	797.7	159.0	26.4	1,454.6	3,039.3
Family TNA ($MM)	3,735	29,992.6	4,959.1	192.9	55,002.9	82,986.0
Age (years)	3,735	9.4	6.5	2.4	17.9	10.2
Expense ratio (%)	3,718	1.4%	1.3%	0.8%	2.0%	0.6%
Turnover ratio (%)	3,712	101.3%	75.7%	25.8%	177.5%	123.8%
Introduced new share class = yes	3,735	33.5%	0.0%	0.0%	100.0%	47.2%
Load fund = yes	3,735	56.9%	79.8%	0.0%	100.0%	45.3%
Short-term trading fee = yes	3,734	66.7%	100.0%	0.0%	100.0%	41.6%
Number of accounts	3,735	41,904.4	4,317.9	58.8	75,923.1	188,533.9
Minimum investment	3,705	138,624.5	1,000.0	50.0	17,767.1	1,002,367.0
Average account size	3,703	3,391,735.0	39,874.6	8,355.2	2,693,630.0	25,700,000.0
Institutional TNA (%)	3,684	27.2%	3.1%	0.0%	100.0%	38.2%
Return (%) -- monthly	3,735	0.27%	0.40%	-0.93%	1.24%	1.32%
Standard deviation (%) -- monthly	3,735	5.41%	4.88%	3.51%	7.98%	2.36%
Carhart alpha (%) -- monthly	3,735	-0.10%	-0.08%	-0.60%	0.37%	0.57%

Table 3
Summary flow characteristics by fund

Table 3 provides the summary statistics for the monthly flows used in this study. The time period covers January 1996-December 2009. The unit of observation is an individual fund. *Inflow* is the monthly new inflows of the fund scaled by the fund's $TNA_{(t-1)}$. *Outflow* is the monthly outflows of the fund scaled by the fund's $TNA_{(t-1)}$. *Net flow* is the difference between the Inflow and Outflow variable. The *standard deviation* and *correlation* of the flows is measured over the life of the fund during our period of study. *Aggregate inflows* and *Aggregate outflows* are the sum of the dollar flows for each month of our sample

Variable	N	Mean	Median	10%	90%	Standard Deviation
NSAR Net Flow (%)	3,735	0.05%	0.02%	-2.30%	2.95%	4.13%
Inflow (%)	3,735	4.67%	3.42%	1.09%	9.00%	4.90%
Outflow (%)	3,735	4.62%	3.14%	1.45%	7.84%	6.56%
σ (%) $_{\text{Net Flow}}$	3,706	5.22%	4.03%	1.33%	9.99%	4.73%
σ (%) $_{\text{Inflow}}$	3,706	4.43%	3.47%	0.85%	9.38%	3.51%
σ (%) $_{\text{Outflow}}$	3,706	4.14%	2.62%	0.88%	9.06%	4.94%
$\rho_{\text{Inflow, Outflow}}$	3,699	19.24%	11.88%	-25.38%	80.16%	39.58%
$\rho_{\text{Inflow, Net flow}}$	3,701	62.82%	72.49%	17.90%	95.53%	32.89%
$\rho_{\text{Outflow, Net flow}}$	3,704	-51.26%	-55.17%	-93.01%	-6.20%	33.68%
Aggregate inflow ($)	168	51,975.72	50,953.00	35,023.44	69,234.63	13,347.16
Aggregate outflow ($)	168	49,090.52	48,850.67	32,296.97	65,913.83	15,088.44

Table 4
Panel regressions of fund flow/performance with risk

Table 4 presents the results from a panel regression of actively managed, equity funds' monthly fund flows on a series of controls and two measures of fund performance: trailing twelve-month return and monthly standard deviation of returns, also estimated over the trailing twelve months. To account for possible convexities in the flow/performance relationship, we include a quadratic term for returns. In models 1, 2, and 3, the dependent variable is the funds' monthly net flow %, monthly inflow %, and monthly outflow % at time (*t*), respectively. The independent variables (definitions in Table 2) are converted to *z*-scores to allow for direct comparison of their economic significance. The interpretation of a coefficient is the change in the dependent variable based on a one standard deviation move in the independent variable. We include year, month, style, and fund fixed effects to control for unobserved heterogeneity across the panel. Our standard errors are clustered at the fund level and robust to heteroskedasticity. ***,**,* represent statistical significance at the 1%, 5%, and 10% level respectively. *p*-values are reported in brackets.

	1	2	3
	Net flow$_t$	Inflow$_t$	Outflow$_t$
Raw return $_{(t-1)}$	0.0139***	0.0087***	-0.0052***
	[0.000]	[0.000]	[0.000]
Raw return^2 $_{(t-1)}$	-0.0024***	0.0005	0.0029***
	[0.000]	[0.707]	[0.007]
$\sigma_{(t-1)}$	0.0013	0.0012	-0.0001
	[0.257]	[0.292]	[0.813]
Log age $_{(t-1)}$	-0.0263***	-0.0141***	0.0121***
	[0.000]	[0.000]	[0.000]
Log size $_{(t-1)}$	-0.0100***	-0.0132***	-0.0032**
	[0.000]	[0.000]	[0.024]
Log family size $_{(t-1)}$	0.0021*	0.0072***	0.0052***
	[0.095]	[0.000]	[0.000]
Log # accounts. $_{(t-1)}$	0.0026***	0.0014***	-0.0011***
	[0.000]	[0.000]	[0.000]
Turnover ratio $_{(t-1)}$	-0.0015**	0.0018***	0.0034***
	[0.033]	[0.002]	[0.000]
Expense ratio $_{(t-1)}$	0.0000	0.0018	0.0018
	[0.951]	[0.105]	[0.120]
Load fund $_{(t-1)}$	-0.0034***	-0.0039***	-0.0005
	[0.001]	[0.005]	[0.698]
Short-term fee $_{(t-1)}$	0.0030***	-0.0063***	-0.0094***
	[0.001]	[0.000]	[0.000]
New share class $_{(t-1)}$	0.0067***	0.0131***	0.0064***
	[0.000]	[0.000]	[0.000]
Style fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes
Observations	270,602	270,602	270,602
R-squared	0.059	0.094	0.038
# of Funds	3,699	3,699	3,699

Table 5
Fund flows for institutional investors

Table 5 presents the results from a panel regression that models the flow activity of retail and institutional investors. The models are identical to that of the models in Table 4, with the key exception being that we interact an institutional dummy variable with each of the independent variables in the model. The *Institution* variable takes on a value of 1 if 100% of the TNA in the fund is identified as institutional by CRSP and 0 if the 0% of the TNA in the fund is identified as institutional by CRSP. In models 1, 2, and 3, the dependent variable is the funds' monthly net flow %, monthly inflow %, and monthly outflow % at time (t), respectively. The first column in each of the models presents the main effects, while the second presents the effect of the interactions with the institutional variable. The continuous independent variables (definitions in Table 2) are converted to z-scores to allow for direct comparison of their economic magnitudes. The interpretation of a coefficient is the change in the dependent variable based on a one standard deviation move in the independent variable. We include year, month, style, and fund fixed effects to control for unobserved heterogeneity across the panel. Our standard errors are clustered at the fund level and robust to heteroskedasticity. ***,**,* represent statistical significance at the 1%, 5%, and 10% level respectively. p-values are reported in brackets.

	1		2		3	
	Net flow	Institution interaction	Inflow	Institution interaction	Outflow	Institution interaction
Institution $_{(t-1)}$	-0.0171		-0.0003		0.0168	
	[0.117]		[0.980]		[0.227]	
Raw return $_{(t-1)}$	0.0130***	-0.0054***	0.0090***	-0.0042***	-0.0041***	0.0012
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.402]
Raw return^2 $_{(t-1)}$	-0.0004	0.0000	0.0056***	-0.0048***	0.0060***	-0.0048***
	[0.755]	[0.977]	[0.000]	[0.003]	[0.000]	[0.000]
σ $_{(t-1)}$	0.0022***	-0.0041***	0.0038***	-0.0055***	0.0016*	-0.0014
	[0.003]	[0.007]	[0.000]	[0.000]	[0.068]	[0.341]
Log age $_{(t-1)}$	-0.0213***	-0.0139***	-0.0150***	-0.0001	0.0063**	0.0138***
	[0.000]	[0.000]	[0.000]	[0.959]	[0.013]	[0.000]
Log size $_{(t-1)}$	-0.0140***	0.0114	-0.0088***	-0.0081***	0.0052***	-0.0195*
	[0.000]	[0.263]	[0.000]	[0.008]	[0.006]	[0.067]
Log family size $_{(t-1)}$	0.0049***	-0.0056	0.0054**	-0.0002	0.0005	0.0054
	[0.009]	[0.196]	[0.015]	[0.955]	[0.789]	[0.170]
Log # accounts $_{(t-1)}$	0.0030***	0.0012	0.0015***	0.0001	-0.0015***	-0.0011
	[0.000]	[0.306]	[0.000]	[0.956]	[0.000]	[0.378]
Turnover ratio $_{(t-1)}$	-0.0030**	0.0071*	0.0024***	-0.0029	0.0054***	-0.0100**
	[0.022]	[0.083]	[0.007]	[0.392]	[0.000]	[0.022]
Expense ratio $_{(t-1)}$	0.0017*	0.006	0.0040**	0.0061	0.0024	0.0002
	[0.086]	[0.189]	[0.013]	[0.153]	[0.131]	[0.974]
Load fund $_{(t-1)}$	-0.0025*	0.0024	-0.0062***	0.0045	-0.0037**	0.0021
	[0.073]	[0.441]	[0.002]	[0.181]	[0.024]	[0.597]
Short-term fee $_{(t-1)}$	0.0012	0.0033	-0.0121***	0.0077**	-0.0133***	0.0044
	[0.353]	[0.257]	[0.000]	[0.025]	[0.000]	[0.215]
New share class $_{(t-1)}$	0.0077***	0.0167	0.0165***	0.0094	0.0088***	-0.0073
	[0.006]	[0.214]	[0.000]	[0.494]	[0.001]	[0.306]
Style fixed effects	Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes	
Month fixed effects	Yes		Yes		Yes	
Fund fixed effects	Yes		Yes		Yes	
Observations	131,434		131,434		131,434	
R-squared	0.044		0.089		0.039	
# of Funds	2,679		2,679		2,679	

Table 6
Does return chasing hurt performance?

Table 6 presents results from calendar-time portfolios comparing the performance of mutual funds based on flow-weighted returns ("new" money) to *TNA*-weighted returns ("old" money) as in Gruber (1996). The estimated alphas measure whether new money is smarter than old money. In Panel A, we separately form portfolios on *Inflows, Outflows,* and *Net Flow* for all funds and then separately for retail-only and institutional-only funds. In Panel B, we repeat the analysis in Panel A by *TNA* quintiles. Panel C provides summary statistics for the quintiles in Panel B. *t*-statistics are in italics throughout.

Panel A: Calendar-time abnormal returns for the overall sample, retail funds, and institutional funds

	(1)		(2)		(3)		(1 - 3)		(2 - 3)	
	Inflow weight		Outflow weight		*TNA* weight		Inflow - *TNA*		Outflow - *TNA*	
	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat
All funds	-0.12	*-1.83*	-0.20	*-3.14*	-0.13	*-2.43*	0.01	*0.22*	-0.07	*-2.09*
Retail	-0.08	*-0.81*	-0.16	*-1.85*	-0.14	*-1.82*	0.06	*1.39*	-0.02	*-0.66*
Institutional	0.05	*0.48*	-0.03	*-0.23*	0.01	*0.10*	0.05	*0.68*	-0.04	*-0.62*
Retail - institutional	-0.13	*-1.50*	-0.14	*-1.63*	-0.15	*-2.30*	0.02	*0.24*	0.01	*0.22*

Panel B:Calendar-time abnormal returns for all funds conditional on size

	(1)		(2)		(3)		(1 - 3)		(2 - 3)	
Size quintile	Inflow weight		Outflow weight		*TNA* weight		Inflow - *TNA*		Outflow - *TNA*	
	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat	alpha	*t*-stat
1 (smallest)	-0.33	*-3.71*	-0.47	*-4.46*	-0.26	*-3.56*	-0.07	*-1.69*	-0.21	*-4.30*
2	-0.10	*-1.09*	-0.29	*-3.01*	-0.13	*-1.77*	0.02	*0.47*	-0.17	*-3.84*
3	-0.16	*-1.49*	-0.30	*-2.94*	-0.11	*-1.52*	-0.05	*-0.90*	-0.19	*-3.97*
4	-0.05	*-0.49*	-0.16	*-1.86*	-0.07	*-1.06*	0.03	*0.60*	-0.08	*-2.79*
5 (largest)	0.00	*0.00*	-0.08	*-1.25*	-0.04	*-0.74*	0.04	*0.97*	-0.04	*-1.38*
5 - 1	0.33	*4.32*	0.39	*4.80*	0.22	*3.93*	0.11	*2.30*	0.17	*3.54*

Panel C: Summary statistics for size quintiles

Size quintile	Monthly raw return (%)		Size (*TNA*)	Inflows	Outflows
	TNA-weight	Equal-weight	($ in 000)	($ in 000)	($ in 000)
1 (smallest)	0.39	0.46	9,879	445	442
2	0.56	0.60	28,843	1,293	1,223
3	0.58	0.63	69,896	2,781	2,638
4	0.62	0.62	181,654	6,680	6,248
5 (largest)	0.58	0.69	1,394,298	33,316	30,931
5 - 1	0.19	0.24	1,384,419	32,871	30,489

Figure 1

Monthly average equity mutual fund flows

The figure shows average monthly new inflows, reinvested inflows, and outflows as a percentage of beginning-of-month TNA. The time period covered is 1996 - 2009. Data are from SEC Form N-SAR filings. The sample contains 3,735 funds and 279,657 fund-month observations.

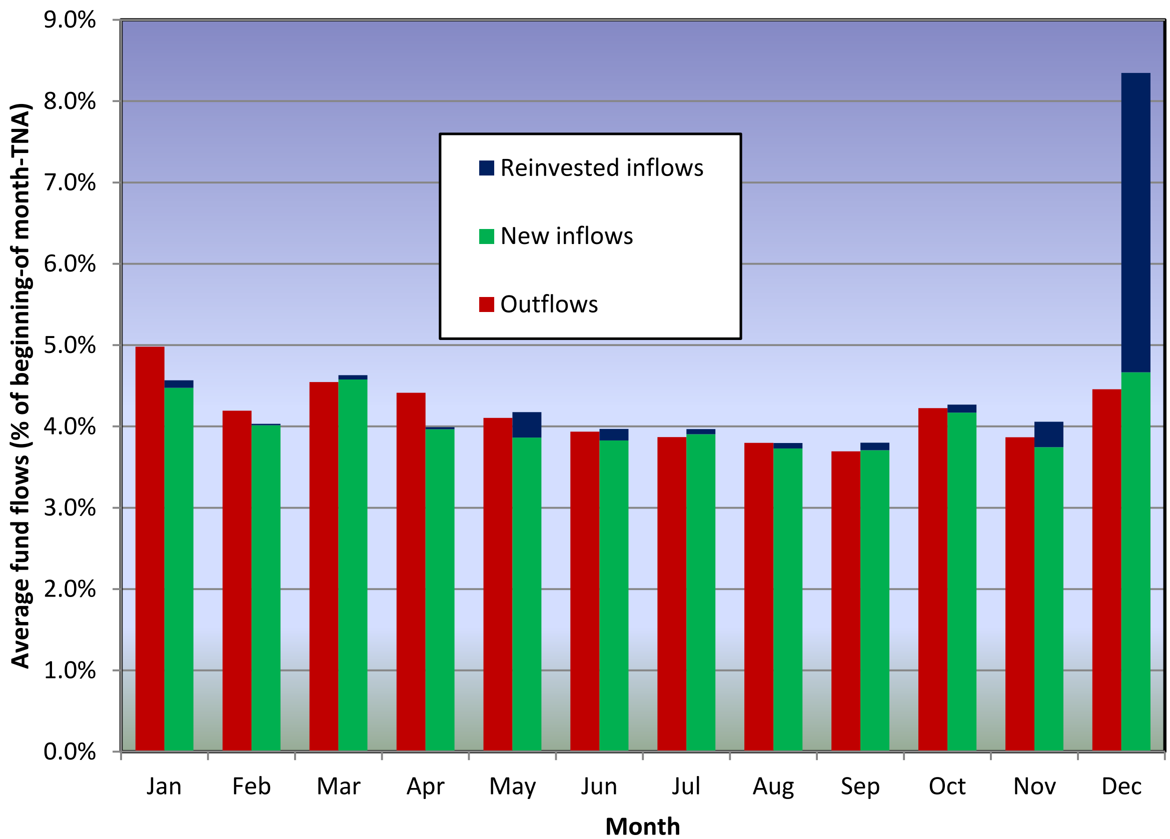
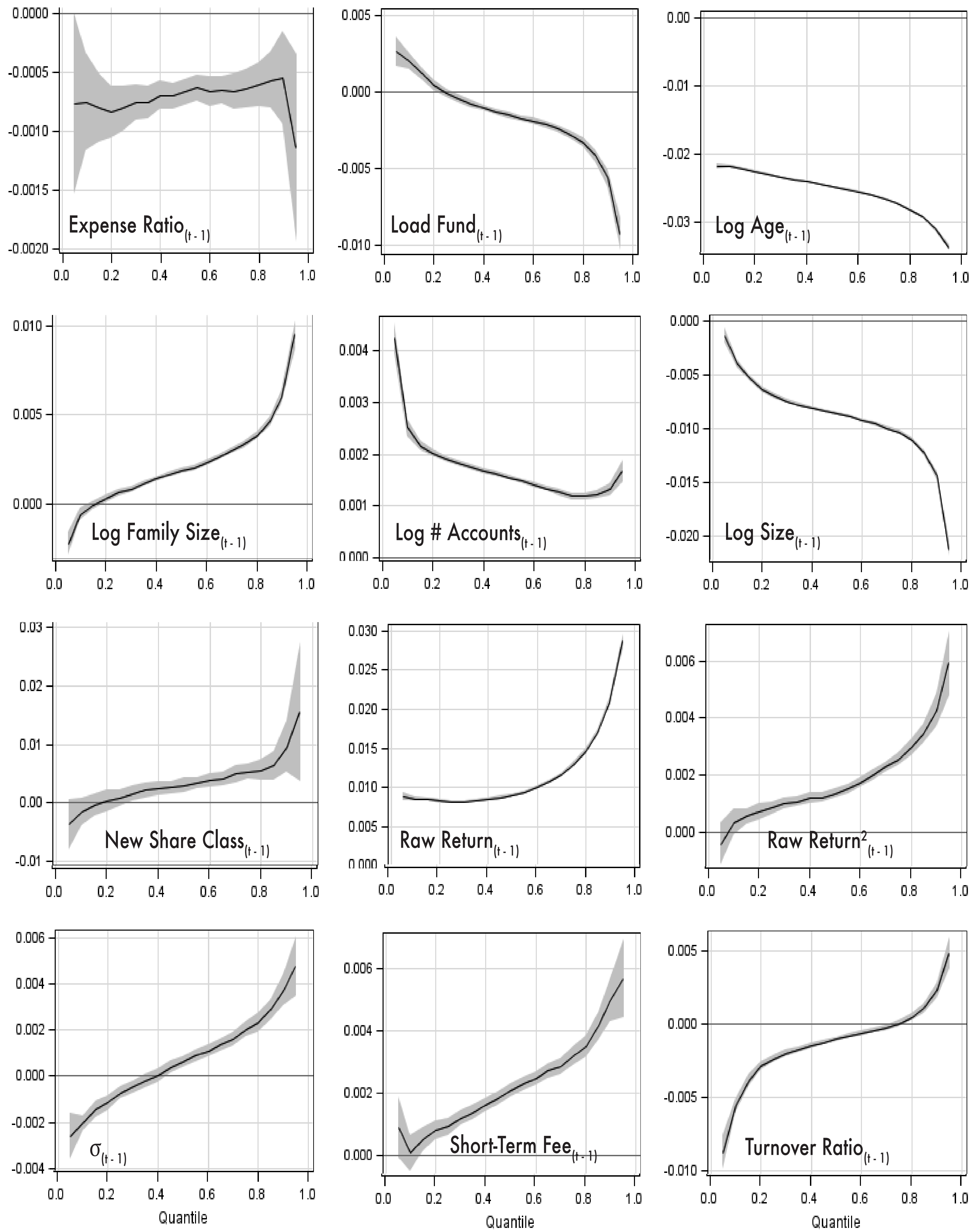


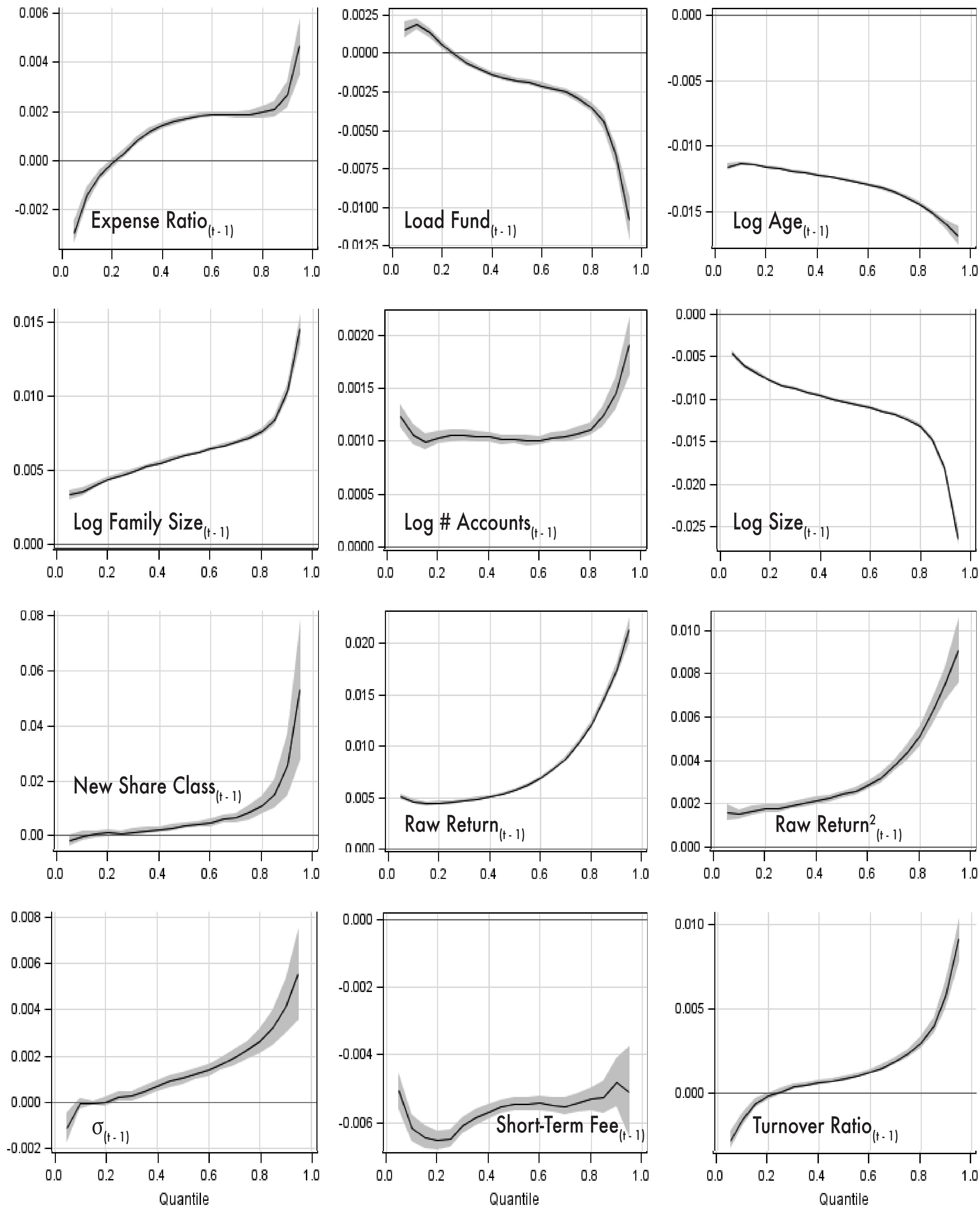
Figure 2
Panel quantile regressions of the flow performance relationship

Figure 2 presents the plots of the estimated coefficients over the conditional quantiles of the flow distribution (Koenker and Bassett (1978)). In Panel A, we estimate the model in eq. (2) for net flows. The model is estimated separately for every 5th percentile of the distribution starting with the 5th quantile and ending with the 95th (19 quanitles in total). Each of the 19 quantile estimates is plotted and a 95 percent confidence interval is included. Though included in the model, we omit the fixed effects (e.g. style) from the plots for brevity. We repeat the analysis on inflows and outflows in Panels B and C, respectively.

Panel A: Net Flows



Panel B: Inflows



Panel C: Outflows

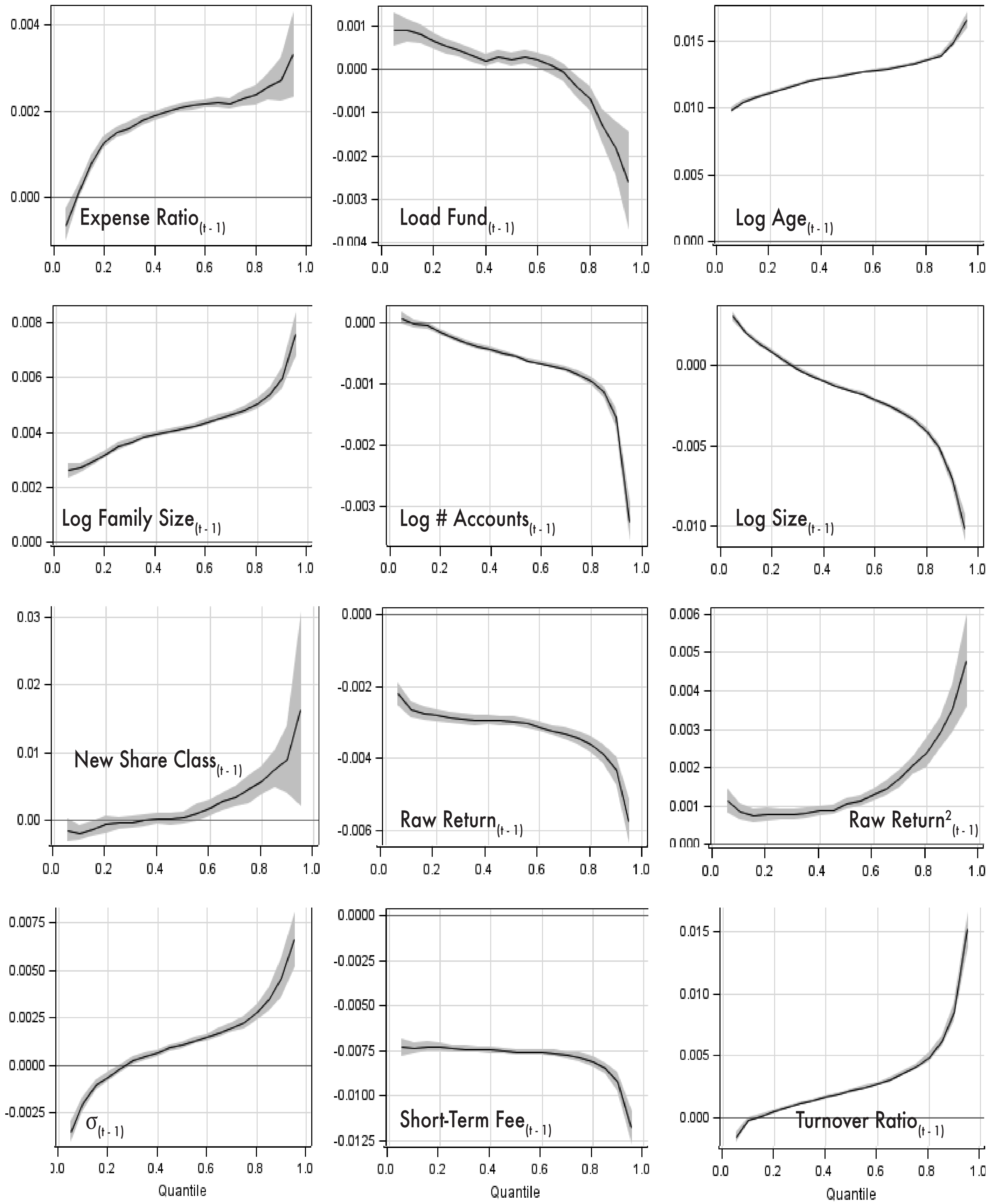
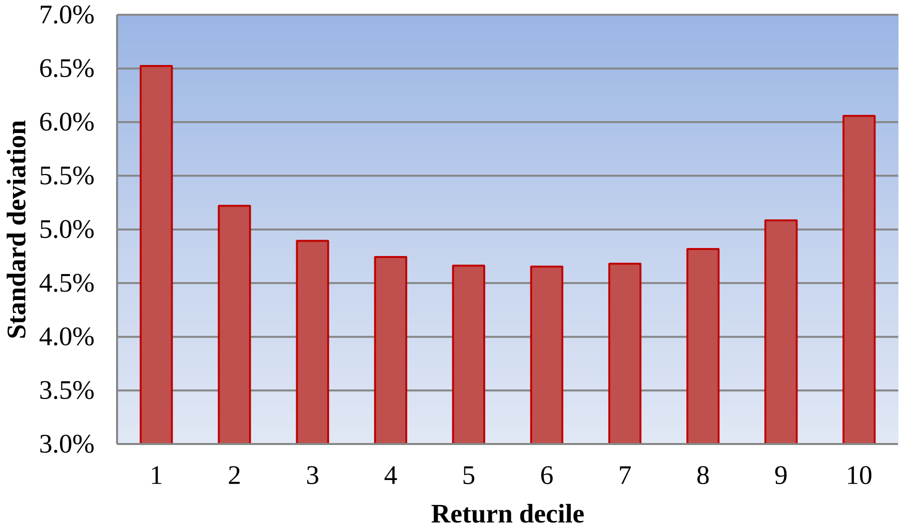


Figure 3

Monthly standard deviation of returns by return decile

The figure shows average standard deviations of monthly returns calculated over a trailing 12 month period for each return decile. For each month in the sample, we form return deciles based on the funds' trailing 12 month return. The time period covered is 1996 - 2009. Data are from SEC Form N-SAR filings. The sample contains 3,735 funds and 279,657 fund-month observations.



Technical Appendix: Building an N-SAR Series Dataset

N-SARs are mandatory semi-annual reports filed with the SEC by management companies. Each filing may contain information about a single fund or a family of related funds. We refer to each distinct fund as a "series". Each N-SAR filing describes one or more series. We construct a dataset which includes one observation for each series and filing.

To extract a dataset of series from N-SAR filings, we

i. acquire a complete list of N-SARs from the EDGAR index;
ii. download the filings;
iii. develop a parser that converts N-SAR filings into a queriable datastructure;
iv. generate a list of N-SAR filings from which our dataset will be drawn
v. traverse the list of filings, querying parsed N-SARs for series information and emitting a tabular dataset

Acquiring the list of N-SARs from the EDGAR Index

We begin by mirroring the EDGAR filing index, which can be downloaded from the SEC's anonymous FTP server. Documentation of the EDGAR filing index can be found at http://www.sec.gov/edgar/searchedgar/ftpusers.htm. We download the entire daily index using the unix utility `wget`:

```
wget -o download_edgar_index.log -r --accept="form.*" ftp://ftp.sec.gov/edgar/daily-index/
```

This yields approximately 1.5G of text files. These files are easily parsed. After scanning past a header to a line comprised only of dashes, we read fixed-width columns.

FIELD	WIDTH
Form Type	12
Company Name	62
CIK	12
Date Filed	12
Path	43

CIK refers to "Central Index Key", a unique identifier of filers defined by the SEC.

We unify the index into a table in a postgres database, inserting each record one at a time. Maintaining a copy of the edgar filing index as a relational database is easy, and convenient for a variety of purposes.

There are two minor issues worth remembering while working with data from SEC index files.

i. Paths are relative to the root of the SEC's FTP server at ftp://ftp.sec.gov, and all paths should begin with "edgar/", the directory that contains all filings. Occasionally "edgar/" is omitted from the paths in the index file, in which case it should be prepended prior to insertion in the database, so that all paths are relative to a consistent base directory.
ii. The SEC index files occasionally contain duplicate records. One must either eliminate these while inserting (for example by enforcing a uniqueness constraint), or else take care to use "select distinct" when querying the index to avoid pulling duplicate records. (We take the latter approach, because we

maintain a field for the name of the source file of each observation in our index so that we can verify the correspondence of our database with the index files from SEC.)

The SQL defining our edgar index table is shown below:

```
CREATE TABLE edgar.filings (
     form_type      VARCHAR(12),
     company_name   VARCHAR(62),
     cik            VARCHAR(12),
     date_filed     DATE,
     path_to_filing VARCHAR(50),
     sourcefile     VARCHAR(20)
)
```

Once the index is populated, generating a full listing of N-SAR files on the SEC's FTP server is trivial:

```
SELECT DISTINCT path_to_filing
FROM edgar.filings
WHERE form_type LIKE 'NSAR%';
```

However, it is usually useful to segregate N-SAR filings by type. There are exactly 10 form types associated with N-SARs, indexed as follows:

EDGAR FORM TYPE	DESCRIPTION
NSAR-A	Semi-annual report for management companies filed on Form N-SAR
NSAR-A/A	Amendment to semi-annual report for management companies filed on Form N-SAR
NSAR-B	Annual report for management companies filed on Form N-SAR
NSAR-B/A	Amendment to annual report for management companies filed on Form N-SAR
NSAR-AT	Transitional semi-annual report for management companies filed on Form N-SAR
NSAR-AT/A	Amendment to transitional semi-annual report for management companies filed on Form N-SAR
NSAR-BT	Transitional annual report for management companies filed on Form N-SAR
NSAR-BT/A	Amendment to transitional annual report for management companies filed on Form N-SAR
NSAR-U	Annual report for unit investment trusts filed on Form N-SAR
NSAR-U/A	Amendment to annual report for unit investment trusts filed on Form N-SAR

Generating a listing of N-SAR files of a specific type, for example 'NSAR-A', then becomes:

```
SELECT DISTINCT path_to_filing
FROM edgar.filings
WHERE form_type = 'NSAR-A';
```

Note: Unit investment trust filings (`NSAR-U` and `NSAR-U/A`) are are not filed in the same structured, parsable format as the other filing types. (They are filed as human readable HTML documents.) At present, we download NSAR-U files, but do not parse them or include them in any of our datasets.

<u>Downloading N-SAR Files</u>

Having produced a list, we then download all available N-SAR filed from the SEC's FTP server. For example, if `path_to_filing` is `edgar/data/100132/0000100132-95-000004.txt`, one might simply run

```
wget ftp://ftp.sec.gov/edgar/data/100132/0000100132-95-000004.txt
```

However, downloading the full set of N-SARs is more challenging than one might expect. First, downloading almost 120,000 files sequentially is time consuming; it's helpful to use a utility that permits concurrent downloads. Secondly, the SEC's FTP server is unreliable and frequently congested. In any given attempt to pull a large list, a sizable fraction of the files will fail to download. We ended up writing (in a mix of Java and Scala) a utility that selects from the index a list of files by form type and then attempts concurrent downloads of only files that have not already been cached. After multiple runs of this utility, we were able to achieve excellent coverage of the `NSAR-A`, `NSAR-B`, and `NSAR-U` filings, and solid coverage of amended filings (`NSAR-A/A`, `NSAR-B/A`, and `NSAR-U/A`). However, coverage of transitional and especially amended transitional filings was much poorer. (Oddly, downloading index files seems much more robust than downloading actual filings. Naive use of `wget` as described above generally succeeds without incident.)

The table below shows the percentage of indexed filings successfully downloaded after 16 attempts to cache each file type:

FORM TYPE	DOWNLOADED
NSAR-A	99.5%
NSAR-A/A	98.8%
NSAR-AT	93.8%
NSAR-AT/A	50.0%
NSAR-B	99.8%
NSAR-B/A	99.6%
NSAR-BT	97.3%
NSAR-BT/A	81.7%
NSAR-U	99.9%
NSAR-U/A	98.4%

Parsing N-SAR Files

We've developed a Java library for parsing N-SAR files. For each downloaded filing, our parser constructs a Java object with a convenient API for querying N-SAR contents. (We can parse all NSAR form types except `NSAR-U` and `NSAR-U/A`.)

Filings on the SEC FTP server are stored as text files in a multipart, SGML-inspired format. The top-level structure of the files is illustrated below. Ellipses ("...") signify material that is omitted for clarity.

```
-----BEGIN PRIVACY-ENHANCED MESSAGE-----
...
...
...

<SEC-DOCUMENT>
<SEC-HEADER>
  ...
</SEC-HEADER>
<DOCUMENT>
<TYPE>NSAR-A
<SEQUENCE>1
<FILENAME>d28130_nsar-a.fil
```

```
<DESCRIPTION>N-SAR (3.0.A)
<TEXT>
  ...
</TEXT>
</DOCUMENT>
<DOCUMENT>
<TYPE>EX-99.77Q1 OTHR EXHB
<SEQUENCE>2
<FILENAME>subwcm.txt
<DESCRIPTION>SUBADVISORY WCM
<TEXT>
  ...
</TEXT>
</DOCUMENT>
<DOCUMENT>
<TYPE>EX-99.77Q1 OTHR EXHB
<SEQUENCE>3
<FILENAME>subrcm.txt
<DESCRIPTION>SUBADVISORY RCM
<TEXT>
  ...
</TEXT>
</DOCUMENT>
</SEC-DOCUMENT>
-----END PRIVACY-ENHANCED MESSAGE-----
```

The first step in parsing filings is simply extracting the header and document sections. We use regular expressions to extract the contents of the sections:

```
// Java regular expression to extract headers
(?s)<(?:SEC|IMS)-HEADER>(.*)</(?:SEC|IMS)-HEADER>

// Java regular expression to extract document sections
(?s)<DOCUMENT>(.*?)</DOCUMENT>
```

Note that the regular expression for extracting the header section matches both `SEC-HEADER` and `IMS-HEADER` tags. In about 5% of the filings, the `SEC-DOCUMENT` and `SEC-HEADER` sections are presented as `IMS-DOCUMENT` and `IMS-HEADER`, but this presents no complication with the accommodative regular expression.

Once the header and document sections are extracted, we identify the N-SAR data simply by searching for the string "<TYPE>NSAR" in each document. We expect that exactly one document section will contain this string, and emit a warning if that assumption is violated. (We store a list of warnings which client applications can access and log.)

At this point, we have our "primary parse", a queriable data structure that contains the following elements.

- The filename (as downloaded from the SEC server)
- The filing's header section
- The N-SAR document section
- A list of all document sections extracted from the filing
- A list of warnings generated during the parse, if any

Next we generate a "secondary parse", which augments the information from the primary parse with

- The Accession Number — a unique identifier given by the SEC to each filing
- The Owner CIK — the unique identifier of the filer
- The N-SAR question data in a format suitable for parsing
- The name and title of the signer of the filed N-SAR

- A mapping between series names and ticker symbols

Some of this information is available from the header section of filings, rather than from the N-SAR document *per se*. So we examine the header. But, a few caveats:

i. Header sections are not always available or parsable, and we tolerate that. All the information in the header can be found elsewhere, except for the mapping between series names and tickers.
ii. Even where headers are present, information for the mapping between series names and tickers may not be. Series names in the header section may not match series as listed or named in the N-SAR data. In general, we extract the mapping between series and tickers, but we rely very little on this information. (Mostly we retain it as a potential source of hints to help us link N-SARs with data from other sources.)

Without further ado, we parse data that is potentially of interest from the header section of the document.


```
0000935069-06-001787.hdr.sgml : 20060629
<ACCEPTANCE-DATETIME>20060629115819
ACCESSION NUMBER:               0000935069-06-001787
CONFORMED SUBMISSION TYPE:      NSAR-A
PUBLIC DOCUMENT COUNT:          6
CONFORMED PERIOD OF REPORT:     20060430
FILED AS OF DATE:               20060629
DATE AS OF CHANGE:              20060629
EFFECTIVENESS DATE:             20060629

FILER:

        COMPANY DATA:
                COMPANY CONFORMED NAME:                 WELLS FARGO FUNDS TRUST
                CENTRAL INDEX KEY:                      0001081400
                IRS NUMBER:                             000000000
                STATE OF INCORPORATION:                 DE
                FISCAL YEAR END:                        1231

        FILING VALUES:
                FORM TYPE:              NSAR-A
                SEC ACT:                1940 Act
                SEC FILE NUMBER:        811-09253
                FILM NUMBER:            06932377

        BUSINESS ADDRESS:
                STREET 1:               525 MARKET STREET
                CITY:                   SAN FRANCISCO
                STATE:                  CA
                ZIP:                    94163
                BUSINESS PHONE:         800-222-8222

        MAIL ADDRESS:
                STREET 1:               525 MARKET STREET
                STREET 2:               12TH FLOOR
                CITY:                   SAN FRANCISCO
                STATE:                  CA
                ZIP:                    94163
<SERIES-AND-CLASSES-CONTRACTS-DATA>
<EXISTING-SERIES-AND-CLASSES-CONTRACTS>
<SERIES>
<OWNER-CIK>0001081400
<SERIES-ID>S000007339
<SERIES-NAME>Common Stock Fund
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000020143
<CLASS-CONTRACT-NAME>Class A
<CLASS-CONTRACT-TICKER-SYMBOL>SCSAX
</CLASS-CONTRACT>
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000020144
<CLASS-CONTRACT-NAME>Class B
<CLASS-CONTRACT-TICKER-SYMBOL>SCSKX
```

```
</CLASS-CONTRACT>
  ...
</SERIES>
<SERIES>
<OWNER-CIK>0001081400
<SERIES-ID>S000007340
<SERIES-NAME>Specialized Technology Fund
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000020147
<CLASS-CONTRACT-NAME>Class Z
</CLASS-CONTRACT>
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000020148
<CLASS-CONTRACT-NAME>Class A
<CLASS-CONTRACT-TICKER-SYMBOL>WFSTX
</CLASS-CONTRACT>
  ...
</SERIES>
  ...
</EXISTING-SERIES-AND-CLASSES-CONTRACTS>
</SERIES-AND-CLASSES-CONTRACTS-DATA>
```

We extract the following information from the header section.

DATUM	JAVA REGULAR EXPRESSION
Accession Number	(?sm)ACCESSION NUMBER:\s+(\S+)\s*$
Owner CIK	(?sm)CENTRAL INDEX KEY:\s+(\d+)\s*$
Series	(?sm)^\s*<SERIES>\s*$(.*?)^\s*</SERIES>\s*$

From each series declared in the SEC header section, we extract the series name and the full set of ticker symbols.

DATUM	JAVA REGULAR EXPRESSION
Series Name	(?sm)^\s*<SERIES-NAME>\s*(.*?)\s*$
Ticker Symbol	(?sm)^\s*<CLASS-CONTRACT-TICKER-SYMBOL>\s*(.*?)\s*$

If the accession number cannot be extracted from the header, it can be extracted from the filename, which is always just the accession number with ".txt" appended. If the Owner CIK cannot be extracted from the header, it can be parsed from the N-SAR data itself, as question 0, part C. Since we have not parsed the question data at this point, or even cleaned it up to render it parsable (see below), we just scrape the answer to question 0, part C from the raw document using the following regular expression.

OWNER CIK REGULAR EXPRESSION	(?sm)^000\s+C000000\s+(\d+)\s*$

If information concerning series (series name and ticker) cannot be extracted from the header, we simply ignore the missing data and continue.

Finally, we complete the secondary parse by extracting the signature information from the NSAR document section and cleaning up the question responses. The box below shows an abbreviated sample of raw response document section containing N-SAR response data.

```
<TYPE>NSAR-A
<SEQUENCE>1
<DESCRIPTION>N-SAR (3.0.A)
<TEXT>
```

```
<PAGE>      PAGE  1
000 A000000 06/30/95
000 C000000 0000100132
000 D000000 N
  ...
012 B000001 84-01761
012 C010001 BOSTON

<PAGE>      PAGE  2
012 C020001 MA
012 C030001 02109
013 A000001 KPMG PEAT MARWICK LLP
  ...
015 D010009 DENMARK
015 E040009 X
015 A000010 BANQUE PARIBAS
<PAGE>      PAGE  3
015 B000010 S
015 C010010 PARIS
015 D010010 FRANCE
  ...
015 E040019 X
015 A000020 NOR/UNION BANK OF NORWAY
015 B000020 S
<PAGE>      PAGE  4
015 C010020 OSLO
015 D010020 NORWAY
  ...
028 G010000     30386
028 G020000         0

<PAGE>      PAGE  5
028 G030000         0
028 G040000     48363
  ...
086 F010000      0
086 F020000      0
SIGNATURE   GERRY MURPHY
TITLE       VICE PRESIDENT
```

We use the following regular expression to pull out the question responses and signature data from the NSAR document.

RESPONSES / SIGNATURE / TITLE REGULAR EXPRESSION	`(?sm)^(000.*)^SIGNATURE\s*(.*?)\s*$\s*TITLE[\t ]*(.*?)\s*$`

We then strip blank lines and notional page separators (lines that begin with "`<PAGE>`"), yielding a clean set of NSAR responses, This completes our secondary parse.

In our tertiary parse, we extract the content of the N-SAR question responses, and render that data conveniently accessible to applications.

The N-SAR answer format is specified in (SEC, 2007). Each response consists of an 11 character question identifier, a space character, and a response. One response is presented per line. Question identifiers are subdivided into the following 5 components:

COMPONENT	COLUMNS	DESCRIPTION
Item Number	1-3	A three digit question number, left-padded with zeros.
Item Subletter	4-5	An optional subletter, from A to ZZ, unnecessary characters are replaced with spaces.
Item Subnumber	6-7	An optional subnumber, or `00`.
Series Number	8-9	A two digit series identifier, `00` for registrant level data, or AA if applicable to all

		series.
Repetition Number	10-11	A two digit repetition number, or `00` if a repetition number is not required.

N-SAR questions might be identified by a simple number (e.g. Question 21), by a number and a letter (e.g. Question 19A), or by a number, letter, and subnumber (e.g. Question 72DD1). Item subnumbers are sometimes not explicitly enumerated on the N-SAR form, but are implied by the order of questions with multiple parts.

Answers to the same question can occur multiple times in an N-SAR filing. Some questions (e.g. Question 20) ask for multiple or repeated answers. Each answer would then be tagged with a distinct repetition number. Other questions (e.g. Question 33) admit only one answer per fund, but since an individual N-SAR can report for a family of related funds, referred to as "series", there can still be multiple responses in a single filing. These responses would be distinguished with distinct series numbers. There can be repeated answers to the same question for multiple series, in which case both repetition and series numbers vary.

The manner in which series are encoded in N-SAR filings admits errors and inconsistencies, and represents a perpetual hassle for the researcher. Series are ostensibly defined in Question 7. Question 7A asks whether a filing is for "a series or multiportfolio company". If the answer to this question is `N`, then in theory series numbers for all questions should be `00`. Question 7B asks the number of series, and 7C asks filers to enumerate all series and supply a number for each that will uniquely identify the series in the current filing.

Unfortunately, much can go wrong with this scheme:

- A nonzero value may be entered for Question 7B, and series may be listed and enumerated in question 7C, even if Question 7A is answered as `N`. For the purpose of identifying series, we always ignore the answer to Question 7A.
- The number of series claimed in Question 7B may disagree with the number of series enumerated in 7C. We identify series based on the data in 7C, and warn if that differs from the number declared in 7B.
- Filings frequently include "unnamed series", that is responses for which a series number is given that corresponds with no name supplied in Question 7C.

To maximize flexibility, our parser captures all available information about series, named and unnamed. However, unnamed series are usually ignored when building datasets. (When unnamed series are included, we end up with a large number of apparent "garbage series" — series for which little or no data is reported and that can not be identified with a known fund.)

Parsing and indexing the N-SAR response data proceeds in several steps:

i. We iterate through the lines of response data, reading each line into a data structure called an `NsarQuestionElement`.
ii. We index each question element read both by series number and by question number (using Java Map objects). We do not index question elements with series number AA, but store them in a separate collection until Step 4.
iii. Once all response lines have been read, we fetch the answers to Question 7, which describe the series in the filing. We store the answers to 7A and 7B (whether the NSAR uses series and how many should be expected). For each series listed in 7C, we examine, we define records mapping series numbers to names. We warn about inconsistencies between the number of series declared and the number of series found, named or unnamed. (Unfortunately, such inconsistencies are very common.)
iv. For each series, named or unnamed, in the filing, we generate a copy of each record we encountered with series number "AA", replacing the wildcard series specifier with a specific series number. We then add these generated responses to our collection of question elements, and our indices by question and series number.

v. Finally, we create a separate, more inclusive collection of series records, combining series we've parsed from Question 7C with unnamed series referenced in the file, which we arbitrarily give names like "`UNNAMED SERIES #4`". (Note that we maintain two collections of series, one that includes only series explicitly declared and named in Question 7, and another which adds to these named series unnamed series referenced in the file.)

NSAR filings are quirky, and attempts to parse lines into question elements may fail for a variety of reasons. We were eager to get as complete a sample as possible, and tried to work around parse errors. Some tricks for maximizing coverage include:

- Question response lines are sometimes surrounded by double quotes, like `"012 B000001 84-01761"`. We test to see if the first and last characters of each line are quotation marks, and if so, we strip quotes prior to reading the question element.
- We allow client applications to specify a set of questions they are interested in. While iterating through responses, our N-SAR parser reads the question number, item letter, and item subnumber first, before trying to parse the full response. If the item is not one of the questions of interest, the parser simply skips the line. This prevents N-SARs from failing to parse due to a problem with a single response that is not required by the researcher. (Questions 0, 1, and 7 must always be parsed, however.)
- Occasionally questions for which a response is left blank are identified only by a three digit question number. We tolerate this.

Ultimately, our tertiary parse offers access to the following, in addition to the data contained by the secondary parse:

i. The set of all question elements contained in a filing, indexed by question number and series number
ii. The set of all series, named and unnamed, defined in the N-SAR filing
iii. The reporting period end date (`A` or `B`, parsed from Question `0A` or `0B`)
iv. The N-SAR type (`A` or `B`, defined by whether Question `0A` or `0B` reports the period end date)
v. Statistics about the number of series named (Question 7C), promised (Question 7B) and referenced (all questions)

Our final NsarParse object augments the tertiary parse with utilities for searching the set of question elements. Searches require that question numbers be specified. Item letters and subnumbers, series numbers and repetitions, can be specified or left blank, in which case they are interpreted as wildcards.

<u>Organizing and Aggregating N-SAR Filings</u>

Ultimately, we are interested not in querying individual filings, but in extracting information associated with an owner CIK during a particular time period. For a variety of reasons, there can be multiple N-SAR filings for the same CIK and time period. For example,

- One registrant (owner CIK) may file on behalf of multiple series whose fiscal years are offset by exactly six months. This requires two filings for each period, one of type `NSAR-A`, one of type `NSAR-B`.
- N-SAR filings may be amended. One `NSAR-A` may be followed by any number of `NSAR-A/A` filings (amendments). One `NSAR-B` may be followed by any number of `NSAR-B/A` filings.

Thus, we aggregate `NsarParse` objects into "buckets" defined by owner CIK, period end date, and N-SAR type (`A`, `B`, `AT`, `BT`). For the purpose of aggregation, amendment filings (whose type ends with "/A") are grouped with their base type (`A/A` with `A`, `B/A` with `B`, `AT/A` with `AT`, and `BT/A` with `BT`).

We categorize each bucket into one of

- `Empty` — No filings available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`
- `Singleton` — One non-amendment filing available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`
- `BaseAndAmendments` — One non-amendment filing and one or more subsequent amendment filings available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`
- `MultipleUnamended` — Multiple non-amendment filings available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`
- `MultipleMixed` — Multiple non-amendment filings plus at least one amendment filing available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`
- `MultipleMisordered` — One non-amendment filing and one or more amendment filings available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`, but the earliest filing is an amendment
- `AmendmentsOnly` — One or more amendment filings but no non-amendment filings available for `(CIK, PERIOD_END_DATE, NSAR_TYPE)`

The only non-empty buckets we expect, and currently the only kind we process, are `Singleton` and `BaseAndAmendments`. However, occasionally buckets of the other categories do turn up. We consider those malformed, and ignore them. (Users may choose to ignore amended filings altogether, in which case we only expect and process `Singleton` buckets.)

For each `(CIK, PERIOD_END_DATE)`, we look for one bucket of type `A` and one of type `B`. If we do not find a non-empty bucket of type `A`, we look for a bucket of type `AT`. If we do not find a non-empty bucket of type `B`, we look for a bucket of type `BT`. We combine all buckets and traverse the collection to extract our dataset.

Buckets are queriable, just like `NsarParse` objects.

For `Singleton` buckets, we simply query the single `NsarParse` object that the bucket contains.

For `BaseAndAmendment` buckets, we merge the collection of `NsarParse` objects as follows:

- In general, we start with the most recent amendment, and check whether the data item we are querying is specified. If it is not, we work backwards, checking the previous amendments until the item is specified or we reach the initial filing. If the item is not available in any amendments or in the initial filing, we return a null value.
- For questions 8, 10, 11, 12, 13, 14, 15, or 25, if any item associated with the question is defined in an amendment (with a value or the token `DELETE`, see below), all items associated with that question are taken from that same amendment. For other questions, we search for each data item independently, going as deeply into the amendment chain as necessary to find a non-null answer.
- Following the querying procedure described above, if a data item resolves to the value `DELETE`, a null value will be returned, even if an older filing contains a non-null value.
- Items from questions 0 through 7 are always taken from the most recent amendment, and are not tested for `DELETE`s. Note that this includes the definition of named series in question 7.

(See page 55 of the N-SAR Form and Instructions *for information on relationship between amendments and earlier filings.)*

<u>Traversing the buckets and generating a tabular report</u>

Using a web-based interface, a user specifies the data she would like to appear in her dataset. Data elements can be specified generally or specifically. For example, "Q7", "Q7B", "Q7B1", and "Q7B1_r2" are all valid specifications. It is the user's responsibility to specify elements that resolve to unique values. (The application will log a warning if a specification is insufficiently precise, and enter a null value for the ambiguous data.)

From each bucket, series information is extracted, and the data requested by the user is queried for each series in the filing. Users may select whether unnamed series should be included (usually they are not) and whether registrant-level information should be included where series-specific information is not available. (Often it is, but users should take care not to treat registrant level data reproduced over multiple series as independent observations.)

For each series in each bucket, a row is generated. All rows contain all data elements specified by the users, as well as the following default items `NSAR_ID`, `NSAR_TYPE`, `OWNER_NAME`, `OWNER_CIK`, `PERIOD_END_DATE`, `SERIES_ID`, `SERIES_NAME`. N-SAR filings that are not subdivided into series generate a single row with `SERIES_ID` and `SERIES_NAME` set to null.

The collection of buckets is subdivided into batches, which are processed concurrently. Output is generated as text, in CSV format. The results of all batches are concatenated, a header row is appended at the beginning, and the generated CSV file is stored in a database and made accessible for download. Results can also be automatically saved into a database table, where they can be accessed in SAS or Stata via ODBC without the hassle of a text-file import.

At present, it takes between three and fifteen minutes to generate a dataset on our multicore Linux server.