Dressing for Style in the Mutual Fund Industry

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Abstract

We define benchmark drift based on changes in a fund's beta relative to its self-promoted benchmark, calculated from the portfolio holdings of both the fund and benchmark. Benchmark drift has a strong adverse impact on mutual fund flows, even when funds beat the benchmark. Moreover, controlling benchmark drift plays a larger role in portfolio risk management than tournament-style behavior. Both external and internal governance mechanisms work to control benchmark drift: funds with greater institutional investment and those in larger fund families demonstrate less benchmark drift and take stronger steps to reduce it once it occurs.

"If a fund manager who usually buys the stocks of small companies starts loading up on blue chips, the advisors object. In fact, they often fire you."

Mario Gabelli, CEO of Gabelli Asset Management Company (*New York Times,* May 26, 1996).

1. Introduction

Style investing, or implementing a preference for certain styles of stocks (e.g., growth versus value), is a common way to narrow investment choices. Even many institutional investors, despite the substantial resources they could apply to individual security analysis, prefer to allocate their investment budget across styles and select portfolio managers with style-specific focus.[1] In fact, Bernstein (1995) attributes the increase in style-oriented portfolio managers to a rise in popularity of style investing among institutional investors during the 1980s. As the opening quote suggests, maintaining style discipline may be critical for style-oriented portfolio managers wishing to attract and retain investors with specific portfolio needs.

On the other hand, fund managers may have risk-based incentives to engage in style drift. It is well known that stronger return performance leads to higher net fund flows. If net flows are convex in performance as found in Chevalier and Ellison (1997), Sirri and Tufano (1998), and Huang, Wei, and Yan (2007), fund managers could have an incentive to drift from their stated style to alter their fund's risk profile and increase the odds of superior performance. This incentive often serves as the motivation for the mutual fund tournament literature, most of which finds that funds alter their risk during the latter part of the calendar year to influence how their year-end performance will compare to that of

[1] Institutional style preferences may have asset pricing implications by affecting the comovement of asset prices (Barberis and Shleifer, 2003). There is also evidence of style preferences impacting the market for corporate control (Massa and Zhang 2009; Burch, Nanda, and Silveri 2012).

peer funds.[2] Although Spiegel and Zhang (2013) challenge the finding that flows are convex in performance on methodological grounds, they note that fund managers may still have career-based (Qui 2003) or compensation-based incentives to alter their fund's risk profile.

One way that funds communicate their selected style to investors is through the choice of their promoted benchmark index. A fund's benchmark sets investor expectations about the fund's risk profile and performance. Thus, how closely the fund's portfolio aligns with the promoted benchmark should be of particular interest to style-oriented investors. In this paper we examine the impact of a fund's portfolio becoming less closely aligned with the benchmark, which we term "benchmark drift," on a mutual fund's net flows and portfolio management. To measure benchmark drift, we track changes in the fund's beta with respect to its benchmark index, i.e., changes in the sensitivity of the fund's return to the benchmark's return.[3]

Our focus on benchmark drift as opposed to measures of style drift in other papers is motivated by the simplicity, ease of interpretation, and visibility of a fund's benchmark index and benchmark beta. For example, industry leaders such as Blackrock, Fidelity, and Vanguard all report a measure of benchmark beta in their fact sheets, web sites, or annual reports. In addition, style-oriented investors that lack the needed expertise to perform more complicated style analysis, or lack the bargaining power to obtain higher frequency portfolio holdings data from funds to do so, can calculate (or often directly observe) benchmark beta to gauge the extent to which a fund operates within its proclaimed style.[4] Thus,

[2]See Brown, Harlow and Starks (1996), Chevalier and Ellision (1997), Koski and Pontiff (1999), Busse (2001), Taylor (2003), Qiu (2003), Kempf and Ruenzi (2008), Chen and Pennacchi (2009), Elton et al. (2010), Huang, Sialm and Zhang (2011), Aragon and Nanda (2012), and Schwarz (2012).

[3]Although our metric highly correlates with the benchmark beta that funds report or that measured by simply regressing fund returns against benchmark returns, as we explain later we use a portfolio-holdings-based methodology to avoid both a fund-level survivorship bias and the stock-level sorting bias discussed in Schwarz (2012).

[4]Given the investment dollars at stake, it is common for funds to comply with requests by major institutional investors or their consultants for relatively high frequency portfolio holdings data.

unlike style drift metrics that are based on a floating reference tied to the fund's prior holdings,[5] benchmark drift is based on an external, highly visible reference point, namely, the benchmark index. Benchmark drift is also useful in helping investors understand whether observed superior performance may simply be due to the fund taking on higher degrees of systematic risk.[6]

To be clear, our focus is not on tracking error in index funds. Instead, our interest is on actively-managed (non-index) funds that investors hope will deliver positive alpha while nonetheless maintaining style discipline. Our sample consists of 1,498 actively-managed equity mutual funds over the years 1990-2012, and we find that investors penalize funds with higher benchmark beta drift through lower net flows. This effect holds after controlling for a variety of fixed effects (including those for the fund and choice of benchmark), as well as prior fund flows and other factors. It is also statistically and economically large, with a one-standard deviation (SD) increase in absolute beta deviation associated with a 1.5% reduction in net flows during the next six months. To put this magnitude into context, the effect on future flows is approximately one-third as large as the effect of a one-SD decrease in a fund's prior six-month excess return over benchmark. We also find the penalty for benchmark drift is larger for funds with higher levels of institutional ownership, consistent with a governance mechanism. Moreover, the net flow reward for stronger return performance is significantly lower for funds with higher levels of benchmark drift.

Retail investors, however, usually can only obtain detailed portfolio holdings through filings with the Securities Exchange Commission (SEC) made twice a year, or at most quarterly.

[5]For example, Wermers (2012) measures style drift by tracking changes in the fund portfolio's exposure to DGTW characteristics from one period to the next. Brown, Harlow and Zhang (2014) take a similar approach but with a focus on the volatility in such exposure. In both papers, the reference is based on the fund's portfolio in a prior period, without respect to whether the fund's portfolio has become more or less similar to specific style benchmark. Unlike benchmark drift, these style drift measures do not yield a directional prediction for how style-oriented investors will react to changes in the fund's portfolio based on style considerations—drift in one direction is treated the same as drift in the other.

[6]See Barber, Huang, and Odean (2015) for evidence that mutual fund flows are sensitive to systematic risk as measured by market beta in the Capital Asset Pricing Model. Berk and van Binsbergen (2015) use fund flows to show that the CAPM is the preferred asset pricing model among mutual fund investors.

In light of these findings, not surprisingly we find that funds with more institutional ownership have lower levels of benchmark drift. We also find that funds in larger fund families have less benchmark drift. This may be due to a strategic focus by large fund families on institutional investor accounts (e.g., 401k plans), or a focus on protecting reputational capital built over many years.[7]

Next we examine the extent to which funds reduce benchmark drift once it occurs. We find that funds with higher levels of benchmark drift in one period show larger reductions in benchmark drift in the next. The methodology we use in this analysis ensures this is not caused by sorting bias or mean reversion in stock-level betas. In separate analysis we also examine portfolios of fund trades, and find that trading choices are made in a way that reduces beta deviation. We demonstrate that this finding is not simply due to funds trading random stocks within their style benchmark.

As changing the portfolio's beta will change its risk, it is important to distinguish benchmark drift management from tournament-style risk management. The tournament literature is premised on the desire to manage calendar-year-end performance, in which funds with superior (inferior) performance in the first half of the year adjust their portfolios' risk exposures downward (upward) in the second half of the year. If our findings are explained by such tournament behavior, we would expect to observe stronger benchmark drift management during the second half of the year than during the first half. Instead, we find that benchmark drift management is consistently strong during both halves of the year. Moreover, although we find evidence of tournament behavior, the ability of benchmark drift management to explain changes in portfolio volatility is several times stronger in economic magnitude than that explained by tournament-style risk management.

[7]For fund-family-wide effects in other contexts, see Chen, Jiang and Goldstein (2008); Elton, Gruber and Green (2007); and Nanda, Wang and Zheng (2004).

Our findings are consistent with anecdotal evidence that benchmark drift management is a significant issue in the mutual fund industry and has important implications for fund flows and portfolio management. On average, mutual fund managers seem well aware of the downside of benchmark drift on fund flows, and take action throughout the year to limit it. Mutual funds indeed dress for style, but unlike in the mutual fund tournament literature in which strong calendar-year effects are observed, window dressing for style takes place throughout the year.

2. Sample, Variables, and Summary Statistics

2.1. Data sources and sample construction

To construct our sample of funds, we merge all U.S. equity mutual funds (except balanced, leveraged, life-cycle and tax-managed funds—these are excluded) from the Morningstar Direct database (including non-surviving funds) with the CRSP Survivorship Bias Free Mutual Fund Database on the basis of CUSIP, and hand-inspect fund names to ensure a match.[8] We then merge the combined dataset with the Thomson Financial CDA/Spectrum fund holdings database on the basis of name, dates, and total assets (we require asset sizes to differ by no more than 20%). These steps result in 1,604 funds.

We next exclude index funds from the sample to avoid funds whose sole objective is to minimize tracking error.[9] Finally, because an important part of our analysis draws con-

[8] We are unable to match approximately 10% of funds in Morningstar to CRSP data—these funds are dropped from the sample.

[9] Including such fund would bias our results in favor of finding that funds manage their benchmark beta to reduce benchmark drift, because of the prominence investors evaluating index funds place on tracking error.

clusions relative to the mutual fund tournament literature, for the sake of comparison with other studies we require that funds report holdings as of the end of June and December.[10]

A fund's benchmark choice is taken as reported in Morningstar, and when a fund specifies both a primary and secondary benchmark we use its primary benchmark. As we will detail later, our analysis requires us to know how a benchmark is constructed in terms of the component assets and their weights. We are able to find accurate benchmark construction data from Standard and Poor's and Russell back to 1990,[11] and thus our sample period begins in 1990. Our final sample consists of 1,498 funds, which we examine over the 1990-2012 period.

As is standard in the literature, when constructing fund returns we combine share classes to construct a single time series of net-of-expense returns. Fund flows are calculated from CRSP (using total net assets and returns, following Sirri and Tufano (1998)). From CRSP we also obtain information on fees and fund characteristics, and we use CRSP data to ascertain the weight of fund assets in a fund's institutional share class (if such a class exists). As described below, we also require stock returns for the component assets in both funds and their chosen benchmarks, and here as well we obtain data from CRSP.

2.2. Benchmark Beta

Benchmark Beta is the main variable of interest in our study, and the most straightforward way to measure it is to regress historical fund returns against benchmark returns. In the context of our research agenda, however, this approach would have two problems. First, it would create a fund-level survivorship bias by requiring that funds have a specified history

[10] Results that do not require such a comparison are similar if all months are included in the analysis.

[11] Constituent information for the Standard and Poor's family of benchmarks is from Compustat, and that for the Russell family of benchmarks is generously provided by Russell Investments. As shown in Sensoy (2009), S&P and Russell benchmarks cover over 90% of managed assets in the mutual fund industry.

of returns over which to estimate beta. Second, when measuring changes in benchmark beta, this method would suffer from the sorting bias explored in Schwarz (2012). In our context, funds sorted into having the most positive returns during the first part of an up-market year would tend to have higher (greater than one) contemporaneously-measured benchmark betas due to the strong return performance of stocks within its portfolio. In turn, any mean reversion in stock-level performance over the second half of the year, mechanically, would result in the fund's benchmark beta declining (due to declines in stock-level betas). This phenomenon could cause us to measure a sorting-bias-induced reduction in benchmark beta towards one.

To avoid these problems, we define *Benchmark Beta* using a portfolio holdings-based methodology that does not require historical fund returns, and when measuring the change in benchmark beta, holds constant the period of returns over which beta is measured. At each holdings reporting period t, we use the relative dollar amounts invested to assign a portfolio weight to each stock owned as of the holdings report date. Holding the portfolio weights constant, we then use stock returns over the prior 36-month period *t-1* to *t-36* to construct 36 hypothetical monthly returns. The same methodology is used to construct 36 months of prior hypothetical returns for the benchmark's portfolio, where the component assets and their weights are based on the benchmark's construction as of the same reporting date, t.

To calculate benchmark beta as of a given holdings reporting date for the fund we then estimate the following OLS regression:

$$RF_t = \alpha \ + \ \beta(RB_t) \ + \ \varepsilon_t, \tag{1}$$

where RB_t and RB_t are the 36 prior hypothetical monthly fund and benchmark portfolio returns, respectively. Thus, β is the fund's benchmark beta as of the holdings reporting period, i.e., the return sensitivity of fund current holdings to the current benchmark, estimated using three years of prior monthly hypothetical returns.

When measuring the change in a fund's benchmark beta (i.e., benchmark drift) from, say, June to December, we first apply the above methodology above to measure β based on December holdings. And when measuring benchmark beta for June, we construct the hypothetical portfolios using June's portfolio allocations, but importantly, the same 36 calendar months of hypothetical returns that were used to measure December's benchmark beta. Thus, the measured change in benchmark beta from June to December will only be due to stock-level weight changes in the fund's portfolio from June to December, and not to potential mean reversion in stock-level betas.

We acknowledge that the portfolio *weight* for each stock will change over time in part due to stock-level return performance. However, fund managers are portfolio management investment professionals who, presumably, pay close attention to portfolio weights. We argue that material changes in portfolio weights due to a lack of rebalancing *should* be reflected in the measurement of benchmark drift because the manager is allowing such drift to occur. Second, to the extent that inertia or trading frictions result in a lack of rebalancing that would otherwise occur, for the subsample of funds with benchmark beta greater than one a lack of rebalancing would exacerbate benchmark drift, not correct it.[12] Despite this exacerbation, we find that funds with benchmark drift manage their benchmark betas towards one regardless of whether their benchmark beta had previously drifted above or below one. In additional

[12]The majority (70%) of years in our sample experience a positive return on the S&P 500 index (other indices in our sample also usually experience positive returns). Thus, in an average year, the strongest performing stocks in a fund with benchmark beta greater than one will have stock-level benchmark betas that exceed one by a greater amount than other stocks in the fund's portfolio. Without fund rebalancing, the investment weights of these stocks will grow larger over time, which will exacerbate benchmark drift even further way from one.

analysis we detail later in the paper, we also document the impact of benchmark drift management on the actual trading decisions that funds make, which abstracts from the effect that failing to rebalance has on benchmark drift.

Table 1 describes our sample over time. Interestingly, the number of funds benchmarked to a particular style (the bottom five groups) as opposed to the broader market (the S&P 500 benchmark group) increased dramatically from 1990 to 2010. As of 1990, 37.3% (47 of 126) of funds in the sample were benchmarked against a style-based index, compared to 64.7% (413 of 638) in 2010.

Benchmark Beta shows a material amount of variation. For example, for funds benchmarked to the S&P 500, in 2010 the 25th percentile is 0.94 and the 75th percentile is 1.13. As we document later, some of this variation is correlated with fund characteristics in predictable ways. The allocation of small-cap funds experiences the largest growth on a relative basis, growing from 10.3% of the sample in 1990 to 24.6% in 2010. For completeness in describing changes in the sample over time we also report fund and family dollar size. *Fund Assets* are obtained from CRSP by aggregating up total net assets (TNA) across all fund share classes. *Family Assets* are obtained by aggregating all assets for a given manager code in Thomson Financial. We do not put these variables in constant dollars, because our results are cross-sectional (not time-series) in nature due to our regressions including time fixed effects.

2.3. Other Variables and Summary Statistics

To measure benchmark drift, we use the absolute value of beta deviation, *Abs(Beta Deviation)*, where beta deviation is the fund's benchmark beta minus one (note that a fund with no benchmark drift would have benchmark beta equal to one). Thus, funds with smaller values of *Abs(Beta Deviation)* have portfolios that more closely track their chosen benchmark style. A fund with a benchmark beta greater (less) than one can reduce benchmark drift by reducing (increasing) its benchmark beta towards one.

One issue we investigate is the extent to which changes in benchmark beta correlate with recent prior performance, similar to the tournaments analysis examined in prior literature. The tournaments literature focuses on changes in total risk, but clearly one way to change a fund's total volatility is to change its beta to the market or benchmark (we note that all benchmarks for our sample funds are positively correlated with the market). Most of our analysis incorporates recent prior performance by including *Excess Return*, where *Excess Return* is the fund's prior six month return net of fees minus the fund's benchmark return over the same period.[13] Monthly fund returns are from Morningstar, returns for S&P family benchmarks are from Compustat, and returns for Russell family benchmarks are provided by Russell.

Part of our analysis investigates whether fund flows are affected by higher levels of beta deviation. Using data in the CRSP mutual fund database, we follow Sirri and Tufano (1998) and construct the variable *Flow* from *t-1* to *t* as:

$$Flow_{t-1,t} = \frac{TNA_t - (TNA_{t-1})(1+R_t)}{TNA_{t-1}}, \tag{2}$$

where TNA_t is the fund's total net assets at time t, and R_t is the fund's return over the prior period.

Institutional Ownership is constructed by aggregating *TNA* across all share classes with the Morningstar Direct code "Inst" and then dividing by *Fund Assets* (funds without an institutional share class have *Institutional Ownership* set to zero). As we note later, we expect

[13] Our results are robust to using a CAPM-adjusted return instead, as would be suggested by the results in Barber, Huang and Odean (2015) and Berk and van Binsbergen (2015).

this measure to understate actual institutional ownership. One way to view *Institutional Ownership* greater than zero, even if assets in this share class are relatively small, is as an expression of the fund's intent to market itself to institutional investors. A fund's *Expense Ratio*, *12b-1 Fee*, and *Turnover* are taken directly from CRSP.

Finally, to measure the total risk of the fund's portfolio we construct *Imputed Volatility*, which is the SD of the fund's 36 hypothetical monthly returns used in the calculation of benchmark beta. Part of our analysis focuses on the change in total fund volatility so we can compare and contrast changes in benchmark beta to changes in fund risk as in the mutual fund tournament literature. For such analysis, similar to when measuring changes in benchmark beta, we use same 36 calendar-months of hypothetical portfolio returns when measuring volatility at two points in time. This results in the change in imputed volatility being due to changes in portfolio composition, not stock-level returns, and thus avoids the sorting bias discussed earlier.

Table 2 provides summary statistics for our variables. The 25th and 75th percentiles in Panel A show that half of the fund observations in our sample have *Benchmark Beta* that deviates from one by more than 10%. Panels B through D show statistics by sample subgroup, as part of the empirical analysis employs similar subsample splits. These panels show that *Beta Deviation* does vary somewhat across these subsamples.

3. Benchmark Drift and Fund Flows

Chan, Chen and Lakonishok (2002) find that style drift occurs more often among poor performing managers of value funds who shift style to be more growth orientated in response to agency considerations. How investors respond in terms of fund flows, however, is an open question. As highlighted in the financial press, portfolio construction considerations suggest that style drift will reduce fund flows, particularly from institutions.[14] However, given the relationship between flow and performance documented by others (e.g., Chevalier and Ellison 1997; Sirri and Tufano 1998; Huang, Wei and Yan 2007) it is possible that investors do not penalize funds with style drift if such drift has resulted in stronger performance. Wermers (2012) finds that funds that chase hot styles enhance their return performance.

To investigate how investors respond to style drift based on our measure of benchmark drift, in Table 3 we regress *Flow* against *Abs(Beta Deviation)*, and the interaction between *Abs(Beta Deviation)* and *Excess Return*. To make clear the timing of the key variables in this regression, consider a fund with *Flow* measured at June 2000. In this example, *Flow* is measured from December 1999 to June 2000, *Abs(Beta Deviation)* is measured at December 1999, and *Excess Return* is measured over the June 1999 to December 1999 period.

The first three columns report regressions on the entire sample, using panel regressions with fixed effects for fund, choice of benchmark, month, and year, and standard errors that are clustered by fund. These regressions show that benchmark drift during one period is followed by lower net flows during the next, even after controlling for a variety of factors. In model (2), a one-SD increase in *Abs(Beta Deviation)* is associated with a 1.53% decrease in fund flows over the subsequent six months, and the p-value for *Abs(Beta Deviation)* is 0.010. This is one-third of the effect of a one-SD decrease in *Excess Return*.

In model (3) we investigate whether benchmark drift is actually rewarded if it results in stronger return performance. Investors may perceive better performance through benchmark drift as an indication of skill, for example. We find, however, that the interaction term *Abs(Beta Deviation)* x *Excess Return* is negative, showing that investors are actually skeptical of stronger performance achieved alongside greater benchmark drift.

[14]For example, see "Fidelity's Managers: Freewheeling No More" in the May 26, 1996 edition of *The New York Times*, and "Style Sticklers: Pension Consultants Policing Fund Managers to See That They Invest as Advertised" from the December 10, 1996 edition of the *Los Angeles Times*.

Models (4)-(6) investigate whether the sensitivity of *Flow* to style drift is stronger in funds with greater institutional investment. Our measure of institutional investment, *Institutional Ownership*, assumes there is no institutional ownership for funds without an institutional share class. This assumption surely understates ownership by institutions, so that we are biasing against finding that institutional ownership matters. Despite this bias, the results are stronger when *Institutional Ownership* is positive. Model (4) shows *Abs(Beta Deviation)* is not significant in the sample in which *Institutional Ownership* is zero, but in model (5) the coefficient and p-value are -0.179 and 0.011, respectively, when *Institutional Ownership* is positive. The SD of *Abs(Beta Deviation)* in the subsample used to estimate model (5) implies that a one-SD in *Abs(Beta Deviation)* is associated with a 2.23% reduction in flows. Thus, funds that are explicitly marketed to institutional investors (as defined by having an institutional share class) experience a more severe fund flow penalty for benchmark drift than funds in general.

It is likely that the causality of this result works in both directions: institutional investors punish funds that have higher levels of benchmark drift with lower levels of investment, and at the same time, funds that wish to attract higher levels of institutional investment are careful to not let their portfolios deviate too far from their promoted benchmark style. That is, persistently low degrees of benchmark drift, on the margin, lead to persistently higher levels of institutional ownership and vice versa. In subsequent analysis we explicitly investigate the factors associated with style drift. Model (6) is at least consistent, however, with some degree of proactivity on the part of institutional investors, as *Abs(Beta Deviation)* x *Excess Return* is highly significant both economically and statistically. Overall, the results with respect to institutional ownership are consistent with an external governance channel in which benchmark drift is noticed and punished by outside investors.

In models (7)-(9) we investigate whether investors respond differently to benchmark drift in funds within small versus large families in terms of assets under management. It is possible, for example, that investors believe larger fund families provide stronger internal governance, and that any style drift tolerated will be well justified. Model (7) shows that funds in the largest quartile of fund families do not suffer a flow penalty for greater style drift, while models (8) and (9) show the opposite for funds in the remaining families. As we show later, funds in larger fund families have less benchmark drift, and thus less cross-sectional variation in drift to explain in the first place. Note that we are careful to control for *Institutional Ownership* in models (7)-(9), because larger families tend to attract greater institutional investment.

In Appendix Table 1 we show our results are robust to the inclusion of other measures of style drift. Specifically, we include the momentum, size, and book-to-market total style drift (TSD) measures in Wermers (2012) and the HSV measure in Brown, Harlow, and Zhang (2014).[15] Our results for *Abs(Beta Deviation)* are qualitatively unaffected, and thus it appears that the style drift captured by benchmark beta plays a distinct role in how investors evaluate funds.

4. Benchmark Drift and Fund Characteristics

We now turn to understanding which funds tend to have greater benchmark drift. The results discussed above establish that institutions, in particular, invest less in funds with greater benchmark drift. Moreover, institutions reduce the flow reward for funds that experience stronger return performance if such performance occurs alongside larger degrees of benchmark drift. This leads us to investigate whether funds with greater institutional ownership will have less benchmark drift in the first place. We also investigate whether funds in larger fund families will have less benchmark drift, which could be the case due to large,

[15] Wermers (2012) examines the relationship between manager characteristics, style drift and performance. In Brown, Harlow, and Zhang (2014), the main focus is on how style drift volatility impacts performance.

well-known families implementing low-drift policies.[16] Of course, it is also possible funds within better-known families are given more leeway by investors to engage in greater degrees of benchmark drift. Ultimately, whether family size affects benchmark drift management, and in which direction if so, is an empirical question.

In Table 4 we regress our main measure of benchmark drift, *Abs(Beta Deviation)*, against *Institutional Ownership* and *Ln(Family Assets)*. Models (1)-(3) estimate a probit model in which the dependent variable is set to one for funds in the top sample quartile for *Abs(Beta Deviation)*, and models (4)-(6) estimate a Tobit model in which the dependent model is simply *Abs(Beta Deviation)*. All models have standard errors clustered by fund. There is strong support for institutional ownership and family size affecting benchmark drift, as greater institutional ownership and belonging to a larger fund family are both are associated with lower values of *Abs(Beta Deviation)*.

5. Regressions Explaining Overall Benchmark Beta Adjustment

In Table 5 we turn to how benchmark drift affects a fund's portfolio management. Given the earlier results showing that fund flows are adversely affected by benchmark drift, we expect mutual funds to manage their portfolios in a way that mitigates such drift. In this section we examine this issue in detail by investigating the conditions under which we observe greater changes in *Benchmark Beta*.

Table 5 reports panel regressions that explain the log change in the absolute value of beta deviation, which is $Ln[(Abs(Beta\ Deviation_{t+1})/Abs(Beta\ Deviation_{t})]$. All models include fixed effects for fund, choice of benchmark, month, and year, and standard errors are clustered by fund. We find in model (1) that the current level of a fund's benchmark drift

[16] Fund family policies have been documented in other contexts, such as fund director ownership (Chen, Goldstein and Jiang 2008).

has a large impact on the extent to which the fund's benchmark drift changes during the next six-month period. Specifically, a one-SD increase in *Abs(Beta Deviation)* in the current period is associated with a 37% lower level of *Abs(Beta Deviation)* in the next period.

An important question is whether the results in model (1) are due to tournament-style behavior in which fund managers with poorer performance during the first half of the year increase risk during the second half. Of course, this question rests on whether June to December tournament-style rebalancing behavior is sufficiently strong in the data to drive the regression estimate of our key covariate. We address the tournament question more directly later, but model (2) does offer one piece of evidence. When we restrict the sample to only include portfolio adjustments from December to June, the coefficient for *Abs(Beta Deviation)* is very similar to that in model (1). As tournament-style behavior would manifest itself in June to December portfolio adjustments (as opposed to in December to June adjustments), observing results that are just as strong in the December to June sample seems inconsistent with tournament behavior explaining the results in model (1).

Our key result is also robust to other subsamples. It is possible that some funds naturally choose to have higher levels of benchmark drift due to their portfolio strategies, such that they do not worry about benchmark drift. This would predict that our results only appear in funds with lower levels of benchmark drift. We find, however, that the main result also holds in model (3), in which we limit the sample to funds with above-median benchmark drift (we note the smaller coefficient for *Abs(Beta Deviation)* is due to *Abs(Beta Deviation)* having substantially larger values in this subsample).

Splitting the sample based on the value of *Benchmark Beta* is also an interesting exercise. Given the positive market performance in most years, and that the market is positively correlated with any of the benchmarks used by the funds in our sample, funds with smaller values of *Benchmark Beta* may have weaker return performance overall and thus have strong performance-related incentives to increase their *Benchmark Beta* (which would work to reduce benchmark drift).[17] Indeed we find that adjustment in *Benchmark Beta* as a function of *Abs(Beta Deviation)* is stronger in the sample of funds with *Benchmark Beta* less than one. However, we continue to find strong results in model (5), which restricts the sample to observations with *Benchmark Beta* greater than one.

Yet another possibility is that funds manage their CAPM betas, and that because equity benchmarks will be correlated with any market benchmark, our results with respect to *Benchmark Beta* are actually the result of CAPM-beta management. Given that the S&P 500 is more commonly used as a market proxy than other benchmarks used by our sample funds,[18] this would predict that our results are stronger for funds that use the S&P 500 as their benchmark. Models (6) and (7), however, actually show that results are stronger in funds that *do not* use the S&P 500 as their benchmark.

6. Regressions Explaining Trade-Based Adjustment in Benchmark Beta

Examining a fund's change in *Benchmark Beta* has the advantage of providing a comprehensive view of how funds manage benchmark drift. However, some of the adjustment in *Benchmark Beta* will be due to stock-level price changes affecting portfolio weights. Fund managers are obviously aware that stock-level price movements alter the asset weights in their portfolios, and thus failing to rebalance is one way managers can purposefully manage benchmark drift. Nonetheless, we also include an analysis limited of active trading behavior, that is, the actual trades that funds make and how such trades affect benchmark drift.

[17]Increasing *Benchmark Beta* will result in stronger return performance in years with positive market performance, and multiple studies document that fund flows positively correlate with fund performance (e.g., Chevalier and Ellison 1997; Sirri and Tufano 1998; and Huang, Wei and Yan 2007).

[18]See the heading in Table 1 for a complete list of benchmark indices used by the funds in our sample.

In Table 6, the dependent variable is (β_{trade}-β_{fund}), which is the weighted average of stock-level *Benchmark Beta* for each stock the fund trades, minus the fund's current portfolio *Benchmark Beta*. The weighting in each trade reflects the size of a trade compared to the total dollar value of all trades that a mutual fund made in a given period. In essence, (β_{trade}-β_{fund}) captures whether a fund's overall trades increase or decrease the portfolio's *Benchmark Beta* relative its current level. Our goal is to investigate whether (β_{trade}-β_{fund}) correlates with *Beta Deviation*. As usual, we cluster standard errors by fund and estimate a panel regression that includes fixed effects.

Panel A reports regressions on samples that align with those used in Table 5. Trades include partial sales and purchases of stocks already in the portfolio, complete liquidations of stocks, and stocks newly purchased by the fund. Our key independent variable is *Beta Deviation* (which is *Benchmark Beta* minus one) without taking the absolute value. This is to maintain clear directional predictions, given that the dependent variable can be positive (for trades that on net increase *Benchmark Beta*) or negative (for trades that on net decrease *Benchmark Beta*). Note that funds with negative *Beta Deviation* that wish to reduce benchmark drift should make trading decisions that have a positive value of (β_{trade}-β_{fund}). In contrast, the portfolio of trades by funds with positive values of *Beta Deviation* should have *negative* (β_{trade}-β_{fund}) if they wish to reduce benchmark drift. Thus, active management to mitigate benchmark drift predicts a negative coefficient on *Beta Deviation*, and this is what we observe in all models.

A potential objection to this evidence is that it could be explained by random purchasing behavior. Consider a fund with new assets to invest, and suppose it chooses new stocks at random from those within the benchmark's portfolio. To illustrate, assume the benchmark index is equally-weighted across its component stocks. In that case, randomly-purchased stocks will have an average beta with respect to the benchmark of one, so that results in

Panel A could result from purposeful trades but in randomly-selected stocks from within the benchmark portfolio.

Panel B addresses this concern in a straightforward manner, by limiting the purchases used in the measurement of (β_{trade}-β_{fund}) to those of additional shares in stocks that the fund already owns (for symmetry we also include partial liquidations only, i.e., complete liquidations are excluded). The idea, for purchases, is to abstract from random purchases stocks in the benchmark's portfolio the fund does not already own by limiting the focus to additional investments in stocks the fund already owns. If the fund's *Benchmark Beta* is not equal to one, then a *random* purchase (more accurately, a purchase chosen randomly on a value-weighted basis) from among the stocks the fund currently owns will not affect its benchmark drift. We would thus observe that (β_{trade}-β_{fund}) is uncorrelated with *Beta Deviation*. As Panel B shows, however, we again observe negative coefficients on *Beta Deviation* in all models.

In Table 7 we perform stock-level regressions that investigate whether the benchmark beta of a stock affects the likelihood of whether it is bought instead of sold. The dependent variable in these regressions is an indicator set to one if the stock is bought and zero if it is sold. The key variable is *Beta Deviation* x $(\beta_{Fund} - \beta_{Stock})$. On the margin, a fund with *Beta Deviation* greater than one should favor lowering its benchmark beta and thus should favor buying (selling) stocks that have $(\beta_{Fund} - \beta_{Stock})$ greater than (less than) than zero. Analogously, a fund with *Beta Deviation* less than one should favor raising its benchmark beta and thus should favor buying (selling) stocks that have $(\beta_{Fund} - \beta_{Stock})$ less than (greater than) than zero. Thus, if beta drift management affects trading decisions, the coefficient on *Beta Deviation* x $(\beta_{Fund} - \beta_{Stock})$ should be positive.

This is indeed what the regressions show. The first model uses ordinary least squares so that fund, month, year, benchmark, and stock industry fixed effects can be included. The rest of the models are probit models.

In the fourth and fifth models we investigate whether the style drift measures in Wermers (2012) and Brown, Harlow and Zhang (2014) affect the likelihood of a buy versus a sell. In these papers, drift is defined based on how the fund's exposure to DGTW factors (Daniel et al. 1997) drifts from one holdings reporting period to the next. Thus, trading to minimize this drift would favor buying stocks in which a stock's DGTW factor portfolio assignment in this period differs as little as possible from the fund portfolio's overall factor exposure ("TSD" in Wermers) in the prior period. We measure the absolute value of the difference in these stock-fund factor exposures, and thus each of the Abs($\cdot$) terms are predicted to have a negative sign.

In the fourth model none of the Abs($\cdot$) variables have the predicted negative sign on their coefficients. Once we add in square terms in model five to control for nonlinearities, the momentum factor variable has the predicted negative sign, but the size factor variable has a positive sign and the book-to-market factor variable is not significant. Thus, the evidence that funds trade to reduce DGTW style factor changes from one period to the next is mixed at best. Note that in models (6) and (7) we again include the benchmark beta variables and find that the significance of the key term *Beta Deviation* x $(\beta_{Fund} - \beta_{Stock})$ holds after controlling for the DGTW factor variables.

7. Regressions Explaining Mutual Fund Volatility Adjustment

Following the work on tournament-style portfolio management by mutual fund managers in Brown, Harlow and Starks (1996), numerous papers examine how equity fund managers respond to performance-related incentives by managing fund volatility (e.g., Chevalier and

Ellison 1997; Koski and Pontiff 1999; Busse 2001; Taylor 2003; Qiu 2003; Kempf and Ruenzi 2008; Chen and Pennacchi 2009; Elton et al. 2010; Huang, Sialm and Zhang 2011; Aragon and Nanda 2012; Schwarz 2012). The main conclusion is that a convex relationship between flows and fund performance induces fund managers to strategically alter the fund's overall risk in the second half of the year in response to fund performance through the first half of the year. Given that there will be a positive correlation between *Benchmark Beta* and a fund's performance (as the average year has a positive market return), a possible concern is that our main results are driven by such tournament behavior.

Although the subsample results in Tables 5 and 6 on December to June changes in *Benchmark Beta* go against the notion that tournament behavior drives our results, in Table 8 we provide further evidence in a more traditional empirical tournament framework. In these regressions, the dependent variable is $Ln(\sigma_{t+1}/\sigma_t)$, which is a holdings-based metric that captures the relative change in total fund volatility over the period measured. As described earlier in motivating how we measure changes in *Benchmark Beta*, here too we avoid the sorting bias by holding constant the calendar months used to measure volatility in both periods.

The first result of note is that our data is consistent with the overall conclusion in the tournaments literature–we do find evidence of tournament behavior in our sample. Models (1)-(4), which measure changes in fund volatility from June to December only, shows that whether we measure performance over the first half the year by the fund's performance percentile rank (within its style objective group as defined by choice of benchmark), or by excess return over benchmark, first-half year performance is significantly and negatively related to changes in volatility in the second half of the year. Moreover, if we estimate the same regressions but using only December to June data, the coefficients on performance are no longer significant (see models (5)-(8)), which is perfectly consistent with portfolio risk adjustment being limited to the second half of the year just as tournament behavior predicts.

The second result of note is that *Beta Deviation* is negative and significant in all models, even after controlling for performance metrics. As documented earlier, benchmark drift causes funds to adjust their *Benchmark Beta* toward one, and because such an adjustment is positively correlated with $Ln(\sigma_{t+1}/\sigma_t)$, we thus observe that the coefficient on *Beta Deviation* is negative as expected. When *Beta Deviation* (which is *Benchmark Beta* minus one) is positive, for example, benchmark drift management predicts the fund will work to lower its *Benchmark Beta*, which in turn would lower the fund's total volatility.

Finally, even though *Beta Deviation* should be a stronger predictor of adjustment in *Beta Deviation* (the left-hand-side variable in Table 5) than in $Ln(\sigma_{t+1}/\sigma_t)$ (the left-hand-side variable in Table 8), it is worth commenting on the economic significance we observe. In both models (2) and (4), a one-SD increase in *Beta Deviation* is associated with a 0.0474 lower value for $Ln(\sigma_{t+1}/\sigma_t)$. This is significantly larger than the economic impact on the change in volatility associated with stronger return performance (the key tournament behavior variable). Note that in model (2), a one-SD increase in *Percentile Rank* is associated with only a 0.0061 lower value of $Ln(\sigma_{t+1}/\sigma_t)$, and the analogous effect of higher *Excess Return* in model (4) is only 0.0087. These results show that benchmark drift management plays an economically more significant role in the changes that funds make in their overall risk levels than tournament-style behavior tied to the performance in the first part of the calendar year.

8. Conclusion

Style investing has become increasingly popular, and with it the importance to portfolio managers of maintaining style discipline. We use a holding-based approach to examine impact of benchmark drift, which we define as drift in a fund's return sensitivity to its promoted benchmark, on a mutual fund's net flows and portfolio management. Our drift metric avoids the type of sorting bias inherent in early mutual fund tournaments literature, and we find that investors (particularly institutional investors) penalize funds with higher degrees of benchmark drift through lower flows, even when the fund returns exceed benchmark returns. External monitoring thus appears to provide a strong incentive for fund managers to limit benchmark drift, and we also document that there is less benchmark drift in funds belonging to large fund families. This could be due to larger fund families targeting institutional investors or wanting to maintain strong brand reputations.

We show that higher degrees of benchmark drift in one period results in a larger reduction in benchmark drift in the next period. This result is not due to tournament-style behavior, is observed in funds regardless of whether their beta with respect to benchmark is greater or less than one, and does not appear to be due to funds managing their CAPM betas. We additionally find that managing benchmark drift has greater ability to explain portfolio changes throughout the year than does tournament incentives in which funds alter overall portfolio risk to influence calendar-year-end returns.

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Table 1. Sample characteristics

This table reports snapshots of the characteristics of our sample over time and across benchmarks. The sample consists of 1498 mutual funds, observed over the period from December 1990 to December 2012 in the Thomson Financial holdings database. *Benchmark Beta* is relative to the mutual fund's benchmark and is calculated from holdings in the Thomson Financial holdings database as described in section 2.2 of the paper. Fund *Assets* is the aggregate value of all stock holdings in the Thomson Financial holdings database for a mutual fund at the specified observation date. *Family Assets* is the aggregate value of all holdings in the Thomson Financial holdings database for a mutual fund's family at the specified observation date. The subsample S&P 500 Funds examines mutual funds which are benchmarked to the S&P 500 index. The subsample Large Cap Funds examines mutual funds which are benchmarked to the S&P 500, S&P 500 Value, S&P 500 Growth, Russell 3000, Russell 3000 Growth, Russell 3000 Value, Russell 1000, Russell 1000 Value, or Russell 1000 Growth indices. The subsample Mid-Cap Funds examines mutual funds which are benchmarked to the S&P 400 Midcap index. The subsample Small-Cap Funds examines mutual funds which are benchmarked to the S&P 600 Small Cap, Russell 2000, Russell 2000 Value, or Russell 2000 Growth indices. The subsample Value Funds examines mutual funds which are benchmarked to the S&P 500 Value, Russell 1000 Value, Russell 2000 Value, or Russell 3000 Value indices. The Subsample Growth Funds examines mutual funds which are benchmarked to the S&P 500 Growth, Russell 1000 Growth, Russell 2000 Growth, or Russell 3000 Growth indices.

		December 1990				December 2000				December 2010			
Subsample	Variable	N	25%	50%	75%	N	25%	50%	75%	N	25%	50%	75%
All Funds													
	Benchmark Beta	126	0.98	1.04	1.14	651	0.83	0.95	1.03	638	0.92	1.01	1.11
	Fund Assets (millions)	126	44	166	407	651	47	194	621	638	81	332	1,120
	Family Assets (millions)	126	204	1,290	2,530	651	374	3,080	9,940	638	961	7,800	40,800
S&P 500 Funds													
	Benchmark Beta	79	1.00	1.07	1.18	267	0.89	0.99	1.07	225	0.94	1.02	1.13
	Fund Assets (millions)	79	49	166	400	267	58	257	869	225	59	272	1,460
	Family Assets (millions)	79	149	1,220	2,530	267	291	2,870	14,000	225	435	6,700	40,800
Large Cap Funds													
	Benchmark Beta	111	1.00	1.06	1.18	459	0.85	0.96	1.03	466	0.95	1.04	1.13
	Fund Assets (millions)	111	50	178	448	459	58	245	916	466	81	337	1,230
	Family Assets (millions)	111	184	1,300	2,880	459	396	4,130	13,500	466	1,040	9,340	42,500
Mid-Cap Funds													
	Benchmark Beta	2	0.33	0.37	0.41	23	0.82	0.98	1.01	15	0.96	1.00	1.11
	Fund Assets (millions)	2	144	216	288	23	30	114	253	15	27	1,020	4,350
	Family Assets (millions)	2	634	1,830	3,020	23	285	2,770	11,900	15	699	21,100	175,000
Small-Cap Funds													
	Benchmark Beta	13	0.88	0.98	1.01	169	0.76	0.93	1.05	157	0.83	0.93	1.00
	Fund Assets (millions)	13	16	47	141	169	30	128	321	157	86	326	864
	Family Assets (millions)	13	352	890	2,070	169	326	2,760	6,260	157	833	5,280	28,100
Value Funds													
	Benchmark Beta	15	0.98	1.00	1.05	91	0.93	0.98	1.03	136	0.89	0.97	1.06
	Fund Assets (millions)	15	24	71	407	91	50	157	459	136	101	337	949
	Family Assets (millions)	15	266	1,300	2,530	91	623	4,450	11,900	136	2,060	13,000	46,600
Growth Funds													
	Benchmark Beta	19	0.98	1.06	1.14	159	0.67	0.84	0.94	154	0.95	1.05	1.15
	Fund Assets (millions)	19	64	178	446	159	53	233	750	154	103	338	1,000
	Family Assets (millions)	19	226	1,660	2,880	159	623	4,480	8,350	154	1,940	13,400	42,500

Table 2. Summary statistics

This table reports summary statistics for the main variables in the study. The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *Benchmark Beta* is a measure of risk relative to a mutual fund's benchmark and is calculated from holdings in the Thomson Financial holdings database as described in section 2.2 of the paper. *Abs(Beta Deviation)* is a measure of the style drift of a mutual fund to its benchmark and is equal to the absolute value of *Benchmark Beta* -1. *Ln(Abs(Beta Deviation*$_{t+1}$*)/Abs(Beta Deviation))* is the logarithm of the ratio of *Abs(Beta Deviation)* over two subsequent periods for a mutual fund and is a measure of the change in the style drift. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Family Assets)* is the logarithm of the aggregate value of all holdings in the Thomson Financial holdings database for a mutual fund's family at an observation date. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Institutional Ownership (%)* is constructed by aggregating CRSP total net assets across all share classes with the Morningstar Direct code "Inst" and then dividing by *Fund Assets*. *Flow* is measured over a 6-month period, defined as in Sirri and Tufano (1998), and is constructed using data from the CRSP Survivorship Bias Free Mutual Fund Database. *Expense Ratio, 12b-1 Fees and Turnover* are all obtained directly from the CRSP Survivorship Bias Free Mutual Fund Database at the share class level and aggregated up to the fund level. *Imputed Volatility* is the annualized volatility of a mutual fund imputed from its holdings. Panel A presents summary statistics for our whole sample while Panel B, C and D examine our summary statistics on subsamples based on *Benchmark Beta*, fund benchmark and *Family Assets* respectively.

Panel A: Complete Sample

	Statistic				
Variable	**N**	**sd**	**p25**	**p50**	**p75**
Benchmark Beta	21,372	0.19	0.90	1.00	1.10
Abs(Beta Deviation)	21,372	0.13	0.05	0.10	0.19
Ln(Abs(Beta Deviation$_{t+1}$)/Abs(Beta Deviation$_t$))	17,026	1.16	-0.47	-0.01	0.44
Excess Return	21,069	0.06	-0.03	0.00	0.02
Ln(Family Assets)	21,246	2.53	19.68	21.68	23.28
Ln(Fund Assets)	21,246	1.99	17.67	19.06	20.39
Institutional Ownership (%)	21,372	0.33	0.00	0.00	0.17
Flow	19,303	0.49	-0.07	-0.01	0.09
Expense Ratio	15,808	0.00	0.01	0.01	0.02
12b-1 Fee	15,808	0.00	0.00	0.00	0.00
Turnover	15,808	0.69	0.33	0.61	1.04
Imputed Volatility	21,372	0.06	0.14	0.18	0.22

Panel B: High versus Low Benchmark Beta Categories

Subsample	Benchmark Beta >1					Benchmark Beta ≤ 1				
	Statistic					Statistic				
Variable	N	sd	p25	p50	p75	N	sd	p25	p50	p75
Benchmark Beta	10,413	0.14	1.05	1.10	1.20	10,959	0.11	0.81	0.90	0.95
Abs(Beta Deviation)	10,413	0.14	0.05	0.10	0.20	10,959	0.12	0.05	0.10	0.19
Ln(Abs(Beta Deviation$_{t+1}$)/Abs(Beta Deviation$_t$))	8,226	1.19	-0.50	-0.03	0.44	8,800	1.13	-0.44	0.00	0.43
Excess Return	10,272	0.06	-0.03	0.00	0.02	10,797	0.06	-0.03	0.00	0.02
Ln(Family Assets)	10,322	2.60	19.88	21.93	23.53	10,924	2.44	19.56	21.50	23.04
Ln(Fund Assets)	10,322	2.05	17.72	19.15	20.49	10,924	1.93	17.63	18.96	20.27
Institutional Ownership (%)	10,413	0.33	0.00	0.00	0.15	10,959	0.34	0.00	0.00	0.21
Flow	9,202	0.51	-0.09	-0.02	0.08	10,101	0.47	-0.06	0.00	0.11
Expense Ratio	7,665	0.00	0.01	0.01	0.02	8,143	0.00	0.01	0.01	0.01
12b-1 Fee	7,665	0.00	0.00	0.00	0.00	8,143	0.00	0.00	0.00	0.00
Turnover	7,665	0.72	0.40	0.68	1.14	8,143	0.66	0.29	0.54	0.95
Imputed Volatility	10,413	0.07	0.15	0.20	0.24	10,959	0.05	0.13	0.17	0.20

Panel C: Benchmark Choice Categories

Subsample	S&P 500 Benchmark					Other Benchmark				
	Statistic					Statistic				
Variable	N	sd	p25	p50	p75	N	sd	p25	p50	p75
Benchmark Beta	8,590	0.20	0.92	1.01	1.12	10,677	0.06	0.95	1.00	1.04
Abs(Beta Deviation)	8,590	0.14	0.05	0.10	0.20	10,677	0.03	0.02	0.05	0.07
Ln(Abs(Beta Deviation$_{t+1}$)/Abs(Beta Deviation$_t$))	6,907	1.09	-0.45	0.00	0.40	8,521	1.37	-0.40	0.27	0.98
Excess Return	8,481	0.06	-0.03	0.00	0.02	10,519	0.05	-0.03	0.00	0.02
Ln(Family Assets)	8,512	2.83	19.12	21.39	23.28	10,614	2.48	19.86	21.84	23.39
Ln(Fund Assets)	8,512	2.16	17.53	19.05	20.60	10,614	1.94	17.80	19.13	20.45
Institutional Ownership (%)	8,590	0.30	0.00	0.00	0.02	10,677	0.34	0.00	0.00	0.24
Flow	7,782	0.43	-0.07	-0.01	0.08	9,665	0.51	-0.07	-0.01	0.09
Expense Ratio	6,066	0.00	0.01	0.01	0.02	7,844	0.00	0.01	0.01	0.01
12b-1 Fee	6,066	0.00	0.00	0.00	0.00	7,844	0.00	0.00	0.00	0.00
Turnover	6,066	0.72	0.28	0.54	0.92	7,844	0.65	0.34	0.61	1.00
Imputed Volatility	8,590	0.06	0.13	0.17	0.20	10,677	0.06	0.14	0.17	0.21

Panel D: Large versus Small Fund Families

Subsample	Above Median Family Assets					Below Median Family Assets				
	Statistic					Statistic				
Variable	**N**	**sd**	**p25**	**p50**	**p75**	**N**	**sd**	**p25**	**p50**	**p75**
Benchmark Beta	10,570	0.18	0.91	1.00	1.10	10,802	0.20	0.89	0.99	1.10
Abs(Beta Deviation)	10,570	0.12	0.04	0.10	0.18	10,802	0.14	0.05	0.11	0.21
Ln(Abs(Beta Deviation$_{t+1}$)/Abs(Beta Deviation$_t$))	8,553	1.16	-0.47	-0.01	0.44	8,473	1.16	-0.47	0.00	0.43
Excess Return	10,424	0.06	-0.03	0.00	0.02	10,645	0.06	-0.03	-0.01	0.03
Ln(Family Assets)	10,570	1.26	22.48	23.29	24.25	10,676	1.81	18.37	19.69	20.80
Ln(Fund Assets)	10,570	1.82	18.92	20.14	21.20	10,676	1.63	16.93	18.08	19.18
Institutional Ownership (%)	10,570	0.31	0.00	0.00	0.15	10,802	0.36	0.00	0.00	0.23
Flow	9,678	0.49	-0.07	-0.01	0.09	9,625	0.48	-0.07	-0.01	0.10
Expense Ratio	8,004	0.00	0.01	0.01	0.01	7,804	0.00	0.01	0.01	0.02
12b-1 Fee	8,004	0.00	0.00	0.00	0.00	7,804	0.00	0.00	0.00	0.00
Turnover	8,004	0.67	0.35	0.63	1.05	7,804	0.72	0.31	0.59	1.03
Imputed Volatility	10,570	0.06	0.13	0.18	0.22	10,802	0.07	0.14	0.18	0.22

Table 3. Regressions explaining mutual fund net flow

This table reports panel fixed effect regressions that explain mutual fund *Flow*. The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *Abs(Beta Deviation)* is a measure of the style drift of a mutual fund to its benchmark and is equal to the absolute value of *Benchmark Beta* -1. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Family Assets)* is the logarithm of the aggregate value of all holdings in the Thomson Financial holdings database for a mutual fund's family at an observation date. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Institutional Ownership (%)* is constructed by aggregating CRSP total net assets across all share classes with the Morningstar Direct code "Inst" and then dividing by *Fund Assets*. *Flow* is measured over a 6-month period, defined as in Sirri and Tufano (1998), and is constructed using data from the CRSP Survivorship Bias Free Mutual Fund Database. *Expense Ratio, 12b-1 Fees and Turnover* are all obtained directly from the CRSP Survivorship Bias Free Mutual Fund Database at the share class level and aggregated up to the fund level. All specifications control for fund, month, year and benchmark fixed effects. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Dependent Variable	**$Flow_t$**								
Subsample	All	All	All	Institutional Ownership (%)			Family Assets		
				Zero	Positive	Positive	Top 25%	Bottom 75%	Bottom 75%
	1	2	3	4	5	6	7	8	9
Abs (Beta Deviation)$_t$	-0.108**	-0.113*	-0.102*	-0.0438	-0.179*	-0.149*	0.0273	-0.156**	-0.144**
	(0.005)	(0.010)	(0.017)	(0.450)	(0.011)	(0.029)	(0.810)	(0.001)	(0.002)
Excess Return$_{t-1}$	0.989**	0.774**	0.993**	0.754**	0.815**	1.320**	0.677**	0.785**	1.061**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)
Abs(Beta Deviation)$_t$ x Excess Return$_{t-1}$			-1.008*			-2.503**			-1.217**
			(0.023)			(<0.001)			(0.007)
Institutional Ownership$_t$ (%)		-0.105	-0.105		-0.241	-0.242	-0.601	-0.0559	-0.0568
		(0.261)	(0.260)		(0.052)	(0.050)	(0.072)	(0.568)	(0.562)
Ln(Family Assets)$_t$		0.016**	0.016**	0.011	0.017	0.017	0.092*	0.011	0.011
		(0.006)	(0.006)	(0.147)	(0.093)	(0.078)	(0.020)	(0.125)	(0.128)
Ln(Fund Assets)$_t$		-0.097**	-0.096**	-0.092**	-0.119**	-0.118**	-0.117**	-0.092**	-0.091**
		(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Flow$_{t-1}$		0.049**	0.049**	0.057*	0.013	0.013	0.015	0.044	0.045*
		(0.002)	(0.002)	(0.041)	(0.468)	(0.476)	(0.523)	(0.050)	(0.049)
Expense Ratio$_t$		-18.906**	-18.747**	-19.315*	-16.110**	-15.703**	-14.401	-22.270**	-22.069**
		(0.001)	(0.001)	(0.031)	(0.006)	(0.007)	(0.321)	(<0.001)	(<0.001)
12b-1 Fees$_t$		-13.706	-13.982	11.223	-34.186*	-35.038*	-58.947	-2.243	-2.692
		(0.261)	(0.250)	(0.482)	(0.043)	(0.037)	(0.100)	(0.873)	(0.848)
Turnover$_t$		-0.011	-0.011	-0.026	0.011	0.012	0.021	-0.021	-0.022
		(0.352)	(0.344)	(0.110)	(0.562)	(0.547)	(0.443)	(0.134)	(0.127)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19,005	12,308	12,308	6,729	5,573	5,573	3,103	9,205	9,205
R-sq	0.037	0.056	0.056	0.051	0.070	0.072	0.054	0.068	0.069

Table 4. Regressions explaining style drift

This table reports Probit and Tobit regressions that explain mutual fund *Abs(Beta Deviation)*. The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *Abs(Beta Deviation)* is a measure of the style drift of a mutual fund to its benchmark and is equal to the absolute value of *Benchmark Beta* -1. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Family Assets)* is the logarithm of the aggregate value of all holdings in the Thomson Financial holdings database for a mutual fund's family at an observation date. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Institutional Ownership (%)* is constructed by aggregating CRSP total net assets across all share classes with the Morningstar Direct code "Inst" and then dividing by *Fund Assets*. Specifications 1-3 present Probit regressions where the dependent variable is a dummy that is equal to 1 if *Abs(Beta Deviation)* is in the top 25th percentile in a period. Specifications 4-6 present Tobit regressions with a left-censoring limit of zero. Coefficients for the marginal effects are reported. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Dependant Variable	**I(Top 25% Abs(Beta Deviation)$_t$)**			**Abs(Beta Deviation)$_t$**		
Model	**Probit**	**Probit**	**Probit**	**Tobit**	**Tobit**	**Tobit**
	1	2	3	4	5	6
Institutional Ownership$_t$ (%)	-0.298**		-0.223*	-0.108**		-0.077**
	(0.001)		(0.016)	(<0.001)		(0.008)
Institutional Ownership Squared$_t$	0.251*		0.168	0.092**		0.058
	(0.017)		(0.106)	(0.004)		(0.071)
Ln(Family Assets)$_t$		-0.009**	-0.009**		-0.004**	-0.004**
		(0.005)	(0.009)		(<0.001)	(0.001)
Excess Return$_{t-1}$	0.116*	0.142**	0.137*	0.105**	0.116**	0.114**
	(0.033)	(0.008)	(0.010)	(<0.001)	(<0.001)	(<0.001)
Ln(Fund Assets)$_t$		-0.007	-0.007		-0.003	-0.003
		(0.089)	(0.099)		(0.062)	(0.066)
N	20,946	20,946	20,946	20,946	20,946	20,946
Pseudo-R Squared	0.004	0.006	0.009			
F Statistic				18.37	29.33	19.98

Table 5. Regressions explaining benchmark beta adjustment

This table reports panel fixed effect regressions that explain mutual fund *Ln(Abs(Beta Deviation$_{t+1}$)/Abs(Beta Deviation$_t$))*. The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *Abs(Beta Deviation)* is a measure of the style drift of a mutual fund to its benchmark and is equal to the absolute value of *Benchmark Beta* -1. *Ln(Abs(Beta Deviation$_{t+1}$)/Abs(Beta Deviation$_t$))* is the logarithm of the ratio of *Abs(Beta Deviation)* over two subsequent periods for a mutual fund and is a measure of the change in the style drift. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Flow* is measured over a 6-month period, defined as in Sirri and Tufano (1998), and is constructed using data from the CRSP Survivorship Bias Free Mutual Fund Database. *Expense Ratio, 12b-1 Fees and Turnover* are all obtained directly from the CRSP Survivorship Bias Free Mutual Fund Database at the share class level and aggregated up to the fund level. All specifications control for fund, month, year and benchmark fixed effects. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Dependent Variable	Ln(Abs(Beta Deviation)$_{t+1}$/Abs(Beta Deviation)$_t$)						
Subsample	All	December to June	Above Median Deviation	Benchmark Beta ≤ 1	Benchmark Beta > 1	S&P 500 Benchmark	Non S&P 500 Benchmark
	1	2	3	4	5	6	7
Abs(Beta Deviation)$_t$	-3.470**	-3.484**	-0.506**	-4.212**	-3.276**	-2.797**	-4.124**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Excess Return$_{t-1}$	-0.0800	-0.0750	-0.136	0.198	-0.110	-0.244	0.124
	(0.631)	(0.746)	(0.420)	(0.426)	(0.683)	(0.292)	(0.591)
Ln(Fund Assets)$_t$	-0.035*	-0.027	-0.006	-0.035	-0.000	0.016	-0.055**
	(0.047)	(0.282)	(0.743)	(0.178)	(0.993)	(0.651)	(0.007)
Flow$_{t-1}$	-0.035	-0.005	-0.013	-0.048	-0.004	-0.065	-0.026
	(0.147)	(0.887)	(0.652)	(0.219)	(0.892)	(0.092)	(0.376)
Expense Ratio$_t$	4.436	9.539	2.301	6.315	-2.641	0.875	10.51
	(0.591)	(0.368)	(0.818)	(0.629)	(0.821)	(0.946)	(0.313)
12b-1 Fees$_t$	-31.815	-14.829	-55.654*	-21.145	-29.824	-19.069	-40.843
	(0.101)	(0.583)	(0.013)	(0.481)	(0.387)	(0.591)	(0.066)
Turnover$_t$	0.023	0.010	-0.108**	0.045	0.006	0.044	0.010
	(0.477)	(0.821)	(0.008)	(0.425)	(0.898)	(0.337)	(0.829)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,858	6,367	6,463	6,611	6,247	4,959	7,899
adj. R-sq	0.089	0.095	0.027	0.100	0.088	0.080	0.103

Table 6. Regressions explaining benchmark beta of trade portfolios

This table reports panel fixed effect regressions that explain mutual fund β_{trade}. The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. $(\beta_{trade} - \beta_{fund})$ is a measure of the weighted average benchmark beta of the stock a mutual fund trades relative to the overall fund *Benchmark Beta*. A positive (negative) value of $(\beta_{trade} - \beta_{fund})$ means a fund's trades are increasing (decreasing) it's overall *Benchmark Beta*. $(\beta_{trade} - \beta_{fund})$ is calculated as described in section 6 of the paper. *Beta Deviation* is a measure of the style drift of a mutual fund to its benchmark and is equal to *Benchmark Beta* -1. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Flow* is measured over a 6-month period, defined as in Sirri and Tufano (1998), and is constructed using data from the CRSP Survivorship Bias Free Mutual Fund Database. *Expense Ratio, 12b-1 Fees and Turnover* are all obtained directly from the CRSP Survivorship Bias Free Mutual Fund Database at the share class level and aggregated up to the fund level. Panel A examines all mutual fund transactions including stock completely liquidated as well as purchased for the first time while Panel B examines only partial sales and purchases of existing stock. All specifications control for fund, month, year and benchmark fixed effects. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Panel A: All mutual fund trades

Dependent Variable	$(\beta_{trade} - \beta_{fund})$ = (\$Buy/\$Trade)$(\beta_{buy}-\beta_{fund})$-(\$Sell/\$Trade)$(\beta_{sell}-\beta f_{fund})$						
Subsample	All	December to June	Above Median Deviation	Benchmark Beta ≤ 1	Benchmark Beta > 1	S&P 500 Benchmark	Non S&P 500 Benchmark
	1	2	3	4	5	6	7
Beta Deviation$_t$	-0.126**	-0.130**	-0.133**	-0.175**	-0.132**	-0.125**	-0.134**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Excess Return$_{t-1}$	0.002	0.041	0.028	0.054	-0.083	0.041	-0.032
	(0.950)	(0.246)	(0.426)	(0.110)	(0.070)	(0.320)	(0.354)
Ln(Fund Assets)$_t$	0.003	0.002	0.004	0.005	0.005	0.003	0.004
	(0.093)	(0.457)	(0.153)	(0.097)	(0.171)	(0.500)	(0.102)
Flow$_{t-1}$	-0.005	-0.001	-0.011*	-0.009	0.000	-0.006	-0.004
	(0.086)	(0.891)	(0.035)	(0.055)	(0.958)	(0.217)	(0.208)
Expense Ratio$_t$	0.211	0.655	0.729	1.360	0.405	-0.307	0.661
	(0.847)	(0.676)	(0.636)	(0.372)	(0.818)	(0.900)	(0.547)
12b-1 Fees$_t$	-1.170	-1.262	-3.530	-1.948	0.103	-0.009	-1.743
	(0.650)	(0.728)	(0.357)	(0.555)	(0.983)	(0.998)	(0.590)
Turnover$_t$	-0.004	-0.004	-0.002	-0.002	-0.006	-0.006	-0.003
	(0.229)	(0.404)	(0.644)	(0.597)	(0.222)	(0.272)	(0.498)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,293	6,139	6,180	6,335	5,958	4,719	7,574
adj. R-sq	0.025	0.028	0.033	0.033	0.017	0.033	0.024

Panel B: All mutual fund trades except liquidations and initial purchases

Dependent Variable	$(\beta_{trade} - \beta_{fund}) = (\$Buy/\$Trade)(\beta_{buy} - \beta_{fund}) - (\$Sell/\$Trade)(\beta_{sell} - \beta f_{fund})$						
Subsample	All	December to June	Above Median Deviation	Benchmark Beta ≤ 1	Benchmark Beta > 1	S&P 500 Benchmark	Non S&P 500 Benchmark
	1	2	3	4	5	6	7
Beta $Deviation_t$	-0.156**	-0.162**	-0.128**	-0.175**	-0.228**	-0.183**	-0.146**
	(<0.001)	(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)	(<0.001)
Excess $Return_{t-1}$	0.030	0.095	0.140	0.078	0.021	0.110	-0.029
	(0.591)	(0.217)	(0.051)	(0.274)	(0.832)	(0.253)	(0.674)
Ln(Fund $Assets)_t$	0.036**	0.028**	0.038**	0.033**	0.045**	0.040**	0.036**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$Flow_{t-1}$	0.035**	0.042**	0.043**	0.047**	0.039**	0.054**	0.027**
	(<0.001)	(0.001)	(0.001)	(<0.001)	(0.002)	(0.003)	(0.005)
Expense $Ratio_t$	7.941**	6.330	6.939*	7.261*	7.323	8.092	7.970**
	(0.001)	(0.051)	(0.027)	(0.010)	(0.064)	(0.097)	(0.006)
12b-1 $Fees_t$	-6.090	-1.617	-7.935	-6.269	-7.332	-2.345	-9.698
	(0.324)	(0.831)	(0.344)	(0.443)	(0.465)	(0.832)	(0.192)
$Turnover_t$	0.005	-0.003	0.006	0.002	0.013	0.009	0.003
	(0.585)	(0.819)	(0.649)	(0.850)	(0.294)	(0.544)	(0.800)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,201	6,100	6,118	6,282	5,919	4,661	7,540
adj. R-sq	0.021	0.033	0.021	0.023	0.021	0.021	0.022

Table 7. Regressions explaining the benchmark beta of individual stock trades

This table reports pooled OLS regressions that explain mutual fund *I(Buy).* The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *I(Buy)* is a variable that takes a value of 1 when the transaction is a buy and a value of 0 when the transaction is a sale. β_{Fund} is the weighted average benchmark relative beta of the stock a mutual fund holds. β_{Stock} is the benchmark relative beta of the stock a mutual fund trades. Trades for the purposes of this table are all sales or purchases of stock a fund makes in a period. β_{Stock} is calculated as described in section 6 of the paper. *Beta Deviation* is a measure of the style drift of a mutual fund to its benchmark and is equal to *Benchmark Beta* -1. *DGTW Size, DGTW Book to Market* and *DGTW Momentum* are stock level characteristics defined as in Daniel, Grinblatt, Titman, and Wermers (1997). *Momentum TSD, Size TSD* and *Book TSD* are measures of style drift in the momentum, size and book-to-market dimensions as defined in Wermers (2012). All specifications control for fund, month, year, benchmark and stock industry fixed effects. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Dependent Variable	I(Buy)						
	OLS	Probit	Probit	Probit	Probit	Probit	Probit
	1	2	3	4	5	6	7
Beta Deviation$_t$	-0.036*	-0.108**	-0.121**			-0.105**	-0.119**
	(0.050)	(<0.001)	(<0.001)			(<0.001)	(<0.001)
β_{Stock}	0.007**	0.005**	-0.003			0.008**	-0.004
	(<0.001)	(<0.001)	(0.567)			(<0.001)	(0.528)
Beta Deviaton$_t$ x $(\beta_{Fund} - \beta_{Stock})_t$	0.074**	0.082**	0.099**			0.080**	0.099**
	(<0.001)	(<0.001)	(<0.001)			(<0.001)	(<0.001)
$(\beta_{Stock})^2$			0.003				0.005*
			(0.125)				(0.040)
Beta Deviation$_t$ x $(\beta_{Stock})^2$			0.022**				0.024**
			(0.005)				(0.009)
Abs (DGTW Momentum$_t$ - Momentum TSD$_{t-1}$)				0.008**	-0.011**	-0.009*	-0.010*
				(<0.001)	(0.006)	(0.011)	(0.010)
Abs (DGTW Size$_t$ - Size TSD $_{t-1}$)				0.002	0.038**	0.034**	0.034**
				(0.790)	(<0.001)	(<0.001)	(<0.001)
Abs (DGTW Book$_t$ - Book TSD$_{t-1}$)				0.008**	0.005	0.005	0.005
				(<0.001)	(0.135)	(0.111)	(0.106)
[Abs (DGTW Momentum$_t$ - Momentum TSD$_{t-1}$)]^2					0.007**	0.006**	0.006**
					(<0.001)	(<0.001)	(<0.001)
[Abs (DGTW Size$_t$ - Size TSD $_{t-1}$)]^2					-0.015**	-0.022**	-0.022**
					(0.007)	(<0.001)	(<0.001)
[Abs (DGTW Book$_t$ - Book TSD$_{t-1}$)]^2					0.001	0.000	0.000
					(0.410)	(0.845)	(0.882)
Fixed Effects	Yes	No	No	No	No	No	No
N	1,375,421	1,671,182	1,671,182	1,347,380	1,347,380	1,235,588	1,235,588
adj. R-sq	0.044	0.001	0.001	0.000	0.001	0.002	0.003

Table 8. Regressions explaining mutual fund volatility adjustment

This table reports panel fixed effect regressions that explain *Ln*(σ_{t+1}/ σ_t). The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *Ln*(σ_{t+1}/ σ_t) is the logarithm of the ratio of *Imputed Volatility* over two subsequent periods. *Imputed Volatility* is a holdings based measure of fund volatility. *Beta Deviation* is a measure of the style drift of a mutual fund to its benchmark and is equal to *Benchmark Beta* -1. *Percentile Rank* is a measure defined on the interval [0,1] where each fund following a benchmark are given a percentile rank based on *Excess Return* over the previous 6-month period. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Flow* is measured over a 6-month period, defined as in Sirri and Tufano (1998), and is constructed using data from the CRSP Survivorship Bias Free Mutual Fund Database. *Expense Ratio, 12b-1 Fees and Turnover* are all obtained directly from the CRSP Survivorship Bias Free Mutual Fund Database at the share class level and aggregated up to the fund level. All specifications control for fund, year and benchmark fixed effects. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

	June to December				December to June			
Dependent Variable	Ln(σ_{t+1}/σ_t)				Ln(σ_{t+1}/σ_t)			
	1	2	3	4	5	6	7	8
Percentile Rank (Winner=1)$_{t-1}$	-0.029**	-0.021**			-0.010	-0.003		
	(<0.001)	(<0.001)			(0.057)	(0.596)		
Excess Return$_{t-1}$			-0.175**	-0.154**			-0.028	-0.004
			(<0.001)	(<0.001)			(0.288)	(0.883)
Beta Deviation$_t$		-0.243**		-0.243**		-0.253**		-0.253**
		(<0.001)		(<0.001)		(<0.001)		(<0.001)
Ln(Fund Assets)$_t$	-0.005**	-0.003	-0.005**	-0.003	0.002	0.004	0.002	0.004
	(0.009)	(0.205)	(0.008)	(0.177)	(0.498)	(0.170)	(0.456)	(0.162)
Flow$_{t-1}$	-0.008*	-0.009**	-0.007*	-0.008*	0.005	0.004	0.004	0.004
	(0.039)	(0.009)	(0.047)	(0.014)	(0.147)	(0.182)	(0.169)	(0.193)
Expense Ratio$_t$	-0.931	-0.077	-0.885	-0.013	-0.188	0.222	-0.175	0.223
	(0.385)	(0.945)	(0.405)	(0.991)	(0.864)	(0.838)	(0.873)	(0.838)
12b-1 Fees$_t$	-4.017	-2.773	-3.929	-2.745	-2.484	-0.656	-2.381	-0.615
	(0.113)	(0.277)	(0.121)	(0.281)	(0.252)	(0.777)	(0.272)	(0.791)
Turnover$_t$	-0.008	-0.008	-0.008	-0.008	-0.009	-0.008	-0.009	-0.007
	(0.079)	(0.081)	(0.094)	(0.087)	(0.053)	(0.093)	(0.059)	(0.096)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6,491	6,491	6,491	6,491	6,367	6,367	6,367	6,367
adj. R-sq	0.152	0.236	0.154	0.239	0.153	0.256	0.153	0.256

Appendix Table 1. Regressions explaining mutual fund net flow

This table reports panel fixed effect regressions that explain mutual fund *Flow*. The sample consists of 1498 mutual funds, observed July and December over the period from December 1990 to December 2012. All variables are expressed as either natural logarithms or winsorized at the 1% level. *Abs(Beta Deviation)* is a measure of the style drift of a mutual fund to its benchmark and is equal to the absolute value of *Benchmark Beta* -1. *Excess Return* is equal to the net of fees return of a mutual fund minus the fund's benchmark return measured over a 6-month period. *Ln(Family Assets)* is the logarithm of the aggregate value of all holdings in the Thomson Financial holdings database for a mutual fund's family at an observation date. *Ln(Fund Assets)* is the logarithm of the aggregate stock holdings of a mutual fund in the Thomson Financial holdings database at an observation date. *Institutional Ownership (%)* is constructed by aggregating CRSP total net assets across all share classes with the Morningstar Direct code "Inst" and then dividing by *Fund Assets*. *Flow* is measured over a 6-month period, defined as in Sirri and Tufano (1998), and is constructed using data from the CRSP Survivorship Bias Free Mutual Fund Database. *Expense Ratio, 12b-1 Fees and Turnover* are all obtained directly from the CRSP Survivorship Bias Free Mutual Fund Database at the share class level and aggregated up to the fund level. *HSV* is a holdings-based style volatility measure defined as in Brown, Harlow and Zhang (2015). *Momentum TSD, Size TSD* and *Book TSD* are measures of style drift in the momentum, size and book-to-market dimensions as defined in Wermers (2012). All specifications control for fund, month, year and benchmark fixed effects. We report p-values robust to intragroup correlation at the mutual fund level in parentheses beneath variable coefficients, **, and * denote statistical significance at the 1%, and 5% levels, respectively.

Dependent Variable				$Flow_t$				
	1	2	3	4	5	6	7	8
Abs (Beta Deviation)$_t$	-0.113*	-0.102*					-0.122**	-0.106*
	(0.010)	(0.017)					(0.010)	(0.013)
HSV_t			-0.053*	-0.053*			-0.052	
			(0.045)	(0.046)			(0.051)	
Momentum TSD_t					-0.012	-0.013		-0.011
					(0.297)	(0.272)		(0.359)
Size TSD_t					-0.022	-0.026		-0.025
					(0.533)	(0.448)		(0.475)
Book TSD_t					-0.021	-0.021		-0.022
					(0.292)	(0.287)		(0.286)
Excess $Return_{t-1}$	0.774**	0.993**	0.696**	0.789**	0.797**	0.800**	0.702**	0.800**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Abs(Beta Deviation)$_t$ x Excess $Return_{t-1}$		-1.008*						
		(0.023)						
HSV_t x Excess $Return_{t-1}$				-0.115				
				(0.510)				
Momentum TSD_t x Excess $Return_{t-1}$						0.162		
						(0.304)		
Size TSD_t x Excess $Return_{t-1}$						0.544		
						(0.119)		
Book TSD_t x Excess $Return_{t-1}$						-0.222		
						(0.371)		
Institutional $Ownership_t$ (%)	-0.105	-0.105	-0.173	-0.172		-0.106	-0.172	-0.104
	(0.261)	(0.260)	(0.137)	(0.140)		(0.253)	(0.141)	(0.264)
Ln(Family Assets)$_t$	0.016**	0.016**	0.023**	0.023**	0.017**	0.017**	0.023**	0.017**
	(0.006)	(0.006)	(0.001)	(0.001)	(0.003)	(0.004)	(0.001)	(0.003)
Ln(Fund Assets)$_t$	-0.097**	-0.096**	-0.100**	-0.100**	-0.093**	-0.093**	-0.101**	-0.094**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$Flow_{t-1}$	0.049**	0.049**	0.046*	0.046*	0.049**	0.049**	0.044*	0.048**
	(0.002)	(0.002)	(0.018)	(0.017)	(0.002)	(0.002)	(0.020)	(0.002)
Expense $Ratio_t$	-18.906**	-18.747**	-20.509**	-20.474**	-18.390**	-18.254**	-20.256**	-18.155**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
12b-1 $Fees_t$	-13.706	-13.982	-18.470	-18.451	-11.982	-12.309	-19.550	-12.804
	(0.261)	(0.250)	(0.230)	(0.231)	(0.321)	(0.308)	(0.204)	(0.290)
$Turnover_t$	-0.011	-0.011	-0.008	-0.008	-0.014	-0.014	-0.008	-0.014
	(0.352)	(0.344)	(0.475)	(0.471)	(0.238)	(0.241)	(0.476)	(0.235)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12,308	12,308	9,786	9,786	12,195	12,195	9,786	12,195
R-sq	0.056	0.056	0.056	0.056	0.053	0.054	0.057	0.054