On the Style-based Feedback Trading of Mutual Fund Managers

Abstract

This paper examines the style-based feedback trading behavior of mutual fund managers. We provide an empirical version of the model for style-switching behavior of Barberis and Shleifer (2003). We find style-based feedback trading for 77% of the funds, half of which is positive- (negative-) feedback trading. There is evidence for "twin-style" switching, in which capital is channeled between value and growth, and between large-cap and small-cap. Growth (value) funds apply more positive (negative)-feedback trading. Funds that switch more aggressively are younger and have higher expense ratios. Finally, we find that positive (negative) feedback trading yields positive (negative) alpha.

JEL Codes: C22; C58; G11

Keywords: Mutual Fund Managers; Style Investing; Feedback Trading.

1. Introduction

In this paper, we examine the style-based feedback trading of US mutual fund managers. Economically, understanding the investment behavior of fund managers is important as they represent a large proportion of investors in the US equity market. At the fund level, the behavior of the fund manager may have a large impact on the performance of the fund and the fees charged. By examining the style-based feedback trading, we make two important contributions to the literature on style investing. First, we develop a new empirical model that directly tests for style-based feedback trading behavior and closely relates to the theoretical framework of Barberis and Shleifer (2003). Second, we empirically implement our model by examining the behavior of mutual fund managers with respect to style investing, style-based feedback trading, "twin-styles", and subsequent (out)performance. We find strong evidence of style-based feedback trading among US mutual fund manager in a way that is consistent with the assumptions of Barberis and Shleifer (2003).

One of the great success stories in finance is the development of the mutual fund industry, which has undergone tremendous growth in the past decades, both in terms of invested capital and the number of funds. As of the end of 2011, the US mutual fund industry maintained $11.6 trillion in assets under management. One-third of this amount is held by US domestic equity funds,[1] which accounts for roughly one-fourth of the US equity market capitalization. Indeed, Gompers and Metrick (2001) illustrate the effect of increased institutional investor demand on asset pricing.

[1] Figures are drawn from the 2012 Investment Company Fact Book.

With this enormous growth in number and diversity, many funds classify themselves into investment styles to provide investors with information about the fund's asset allocation. These styles have grown out of the popularity of certain investment strategies among mutual fund investors, such as growth or value stocks and small- or large-cap stocks (Teo and Woo, 2004). Because these strategies are selected for their (perceived) ability to produce positive alpha, pursuing such a strategy should play a major role in determining the returns that a fund generates. However, as Barberis and Shleifer (2003) note, the returns to particular styles are not constant and may be thought of as following a life cycle in which returns may change from outperforming initially to underperforming as market conditions change or the characteristic is priced out of the market. Thus, returns for funds following a particular style will be driven by the performance of that style to a great degree.

An important element in this context is determining the effect that changes in style performance will have on funds and on the commitment of these funds to strictly follow a particular style. Competition between mutual funds for fund flow is fierce, and flows are significantly affected by a fund's recent performance (Sirri and Tufano, 1998). As a result, there are considerable incentives for funds to outperform other funds with similar styles.[2] One way to achieve outperformance is to alter investments and increase exposure to styles that are expected to perform better. Evidence for such behavior has been documented by several studies, including Cooper et al. (2005), who find that funds have a tendency to change their name to take advantage

[2]For instance, Brown, Harlow, and Starks (1996) show that mutual funds engage in so-called "tournament behavior" in which funds take on additional risks in later evaluation periods if they are being outperformed by their peers. In addition, Chevalier and Ellison (1997) illustrate that the convex shape of the flow-performance relationship causes fund managers to adjust the riskiness of the fund based on year-to-date return.

of current "hot" investment styles, and by Wermers (2012), who shows that there is 'style drift' in the holdings of mutual funds, which is partly deliberate and is chasing style returns.

Chasing style returns is consistent with the theoretical "style investing" model of Barberis and Shleifer (2003), in which investors classify assets into styles and make allocations at the style level by acting as feedback traders, comparing the past performance of different investment styles. This model explains various stylized facts observed in financial markets (such as style momentum and excess comovement of assets within a style) – it connects investor behavior and market characteristics.

Although the empirical predictions of Barberis and Shleifer's (2003) model have been tested by several studies,[3] we are not aware of any study that directly examines the behavior of mutual fund managers regarding style investing, style-based feedback trading, and "twin-styles" following the model of Barberis and Shleifer (2003). Based on Froot and Teo (2008), who find that institutional investors allocate more at the style level than at the stock level, we postulate that fund managers exhibit similar behavior in terms of allocating assets to different styles and acting as style-based feedback traders.[4]

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[3]Teo and Woo (2004), for instance, find evidence for style-level momentum. In addition, Froot and Teo (2008) find evidence of institutional investors making decisions at the style level. Pomorski (2004) studies the predictions of the model regarding fund flows.

[4]This paper relates to several studies on investor behavior (i.e., feedback trading). An important contribution in this respect comes from Grinblatt, Titman and Wermers (1995), who find that 77% of mutual funds have a tendency to buy past winning stocks. Bange (2000) shows that stock portfolio adjustments of individual investors reflect past market movements. In addition, Keim and Madhaven (1995) document both momentum and contrarian trading by institutional investors. Choe, Kho, and Stulz (1999) and Froot, O'Connell, and Seasholes (2001) report feedback trading by institutional investors at the country level. Goetzmann and Massa (2002) examine trading behavior of individual investors in index funds and find that certain investors act as positive-feedback traders, whereas others act

We implement the model of Barberis and Shleifer (2003) empirically by using a discrete choice model following Manski and McFadden (1981) and employing concepts of the adaptive rational equilibrium framework proposed by Brock and Hommes (1997). These latter authors propose a model in which economic agents use predictors (i.e., functions of past information) and choose between these predictors using a discrete choice model, selecting the predictor – or putting more faith in the predictor – that has produced the highest profit or the lowest forecast error in the recent past. This generates a dynamics where, over time, agents switch between different predictors and adjust their demand for assets accordingly.[5] This model can be implemented to examine style investing and style based feedback trading in general, however, in this paper we implement the model to US domestic equity funds. Specifically, we estimate a model in which fund returns have time-varying exposures to four benchmark portfolios (or four styles: large-cap, small-cap, value, and growth), where the time variation is conditional on lagged style returns.

We use the survivorship-free CRSP mutual fund database over the period December 1961-September 2010 to examine switching behavior in US domestic equity funds. We classify funds into different styles using the Lipper Classification code based on size (Large-, Multi-, Mid-, and Small-cap) and value-growth orientation (Value, Center, and Growth). This produces a

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as negative-feedback traders. In an extension, Blackburn et al. (2011) study the trading behavior of individual investors in style and multi-style funds (value, growth and value-growth funds). They find that investors adopt different trading strategies depending on the characteristics of the assets being traded; growth investors tend to follow momentum buy strategies, and value investors tend to follow a contrarian buy strategy.

[5]See Brock and Hommes (1998) for the complex dynamics that such a model can generate in asset prices.

4 × 3 matrix of 12 different styles. To assess the switching behavior of fund managers, we utilize the following four benchmark portfolios/styles from Kenneth French's website: large-value, small-value, large-growth, and small-growth.[6] The selection of these four styles enables us to examine the style-based feedback trading behavior of fund managers in both the size and value-growth dimensions jointly and separately.

Our paper produces several new and important findings with respect to style-based feedback trading in mutual funds. First, we document that over 50% of the funds in our most basic specification – and 77% in the more complex specification – engage in some form of style-based feedback trading. These results corroborate the findings of Froot and Teo (2008), who also find strong support for style-level trading by US domestic equity fund managers, and the findings of Grinblatt, Titman, and Wermers (1995), who find that momentum investing occurs in 77% of index funds. Notably, we find that fund managers act as positive-feedback or momentum traders (as suggested by Barberis and Shleifer, 2003) but that a considerable number of fund managers act as negative-feedback or contrarian traders.[7] These findings have also been observed in the trading behavior of individual investors in index funds (Goetzmann and Massa, 2002) and style funds (Blackburn et al., 2013) but have not yet been documented in the trading behavior of fund managers. Wermers (2012) notes that style drift is partly caused by active management and that managers tend to be "style chasers"; this is in line with our findings of style-based feedback trading. We deviate from Wermers (2012) by giving more structure to the

[6]Data are available from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html. The selection of these four styles allows for switching in the size and value-growth dimension.

[7]We follow Goetzmann and Massa (2002) in our definitions of momentum and contrarian traders, where a momentum trader is defined as a trader who buys after a recent price increase and a contrarian trader buys after a recent price decrease.

active-style drift in the form of "twin-style" feedback trading, as suggested by Barberis and Shleifer (2003), and by relating this to fund characteristics, performance, and fund flows.

Second, we examine how the style-based feedback trading strategy is financed. That is, given the fact that we study domestic equity funds, which have a long-only exposure to domestic equity of 100%[8], an increased investment in one style must be at the expense of another style. Consistent with Froot and Teo (2008) and following Barberis and Shleifer (2003), we find support for the existence of so-called twin styles, in which investors switch between styles at opposite ends of the spectrum. Thus, for example, an increase in the allocation to value stocks is financed by a decrease in the allocation for its twin style, growth stocks. For the funds that engage in style-based feedback trading, the majority tend to do so in both the value-growth and the size dimension. Moreover, we find that fund managers engage in twin-style trading either as positive- or negative-feedback traders, depending on the investment style of the fund.

Third, we find that style-based feedback trading, i.e., being a positive- or negative-feedback trader, strongly depends on the fund's proclaimed investment style; managers of growth funds tend to base their switching strategy on a positive-feedback rule (i.e., increasing exposure to styles that have performed relatively well in the recent past), whereas managers of value funds tend to base their switching strategy on a negative-feedback rule (i.e., increasing exposure to styles that have performed relatively poorly in the recent past). This has been

[8] In practice, exposure is slightly less than 100% as funds hold a small percentage of assets in cash. This does not change the reasoning, though.

observed in the trading behavior of individual investors (Blackburn et al., 2013), but has not yet been documented in the behavior of institutional investors.

Fourth, when we examine the relationship between fund characteristics and style-based feedback trading in a cross-sectional test, we find that younger funds and funds with higher total expense ratios engage in more aggressive feedback trading. For funds that switch aggressively in the size dimension, we also find a significantly positive relationship with the fund's turnover. Subsequently, we evaluate whether style-based feedback trading leads to increased outperformance or attracts fund flows.[9] We find that style-based feedback trading affects outperformance. Specifically, we find that positive (negative) feedback trading yields positive (negative) outperformance. The outperformance of a positive-feedback strategy decreases as the period over which the past performance is being evaluated increases, whereas the underperformance of a negative-feedback strategy decreases as the lookback period increases in length. These findings are consistent with the short-run momentum versus long-run mean reversion dynamics demonstrated by Jegadeesh and Titman (1993). These results also relate to Brown et al. (2011), who study style switching (measured by style volatility) and relate this to risk-adjusted outperformance of mutual funds. Contrary to Brown et al. (2011), we find that funds that have a particular form of style volatility actually have higher risk-adjusted performance. We further extend their work by showing that style volatility may be split into

[9] Several studies have examined style timing in mutual funds; however, evidence of whether this style timing is profitable is mixed. For example, Swinkels and Tjong-A-Tjoe (2007) examine three styles, market timing, value-growth, and size; they find profitable switching with respect to market timing and value-growth but not size. Budiono and Martens (2009) test a model with all three styles, market timing, value-growth, and size, and find that managers with time styles generate significant outperformance. Grinblatt et al. (1995) find outperformance of momentum traders compared to other funds. By contrast, Brown, Harlow, and Zhang (2011) show that funds that switch aggressively (i.e., have high style volatility) underperform relative to funds with less style volatility on a risk-adjusted basis.

positive- and negative-feedback trading, and show that both these strategies have a different effect on risk-adjusted outperformance.

The remainder of the paper is organized as follows. Section 2 presents our feedback trading model. In Section 3, we explain the data and methodology applied to estimate the model, and Section 4 presents the style-switching results. Section 5 relates style switching to fund characteristics, and Section 6 relates style switching to performance. Section 7 concludes.

2. Model

Barberis and Shleifer (2003) propose a model of style investing in which the market is populated by investors who switch among investment styles based on the past comparative performance of these styles (referred to as switchers) and fundamental traders who act as arbitrageurs. In this section, we develop an empirically testable model following Barberis and Shleifer (2003) in which mutual fund managers – instead of individual investors – switch between investment styles based on the styles' comparative past performances and thus act as style-based feedback traders.[10]

According to Barberis and Shleifer (2003), switchers allocate more capital to a particular style if it performed comparatively well in the recent past and finance this by allocating less to styles with comparatively poor past performance. These switchers are assumed to have a specific look-back period over which they compare the relative performances of different investment

[10]Note that we use the term switching rather loosely here. Mostly it refers to partial reallocation of capital across different investment syles.

styles. Furthermore, they have a specific degree of style persistence – how sensitive they are to differences in comparative past performances of investment styles. These investors are also less willing to switch between asset classes (although they are willing to switch between styles); thus, investors may be willing to switch between value and growth, but are less willing to switch between equities and bonds, for instance. This implies that switching between styles is mostly self-financed within a specific asset class. Finally, Barberis and Shleifer (2003) suggest that these investors choose to switch between so-called twin-styles, e.g., an increased allocation to growth stocks is financed by a decreased allocation to value stocks, and an increased allocation to small-cap stocks is financed by a decreased allocation to large-cap stocks.

We empirically model style switching using the multinomial choice model as introduced by Brock and Hommes (1997). Brock and Hommes (1997) consider a market for a single asset in which investors can switch between different trading strategies over time based on their relative performance in recent periods. Deciding to switch between these strategies utilizes a multinomial choice function with several desirable features. First, it introduces continuous time-varying exposures to different investment styles that permit transforming a model with static exposures into a dynamic model. Second, this function is flexible and may include any variable that triggers fund managers to change their investment style. In this paper, we use the past performance of different investment styles to assess whether fund managers engage in style-based feedback trading. Third, this function leads to a parsimonious model specification, which (in the simplest specification) consumes only one additional degree of freedom (compared to a static specification).

We model the style-based feedback trading of mutual fund managers as follows. At each point in time, fund managers examine the past performance of K different investment styles, where $k = 1, \ldots, K$. We define the past performance of style k as

$$\pi_{t-1}^{k} = \sum_{j=1}^{J} r_{t-j}^{k} , \tag{1}$$

where r_t^k is the return on investment style k in period t, π_{it-1}^{k} is the past performance measure of investment style k in period t – 1, and j is the number of periods that the fund manager looks back ($j = 1, \ldots, J$).[11]

Following Brock and Hommes (1997, 1998), we assume that switching between styles follows a multinomial switching rule that compares the performances of the various investment styles. According to this switching rule, the weight that manager i puts on investment style k is defined as

$$w_{it|t-1}^{k} = \frac{\exp\{\gamma_i(\pi_{t-1}^{k})\}}{\sum_{k}\exp\{\gamma_i(\pi_{t-1}^{k})\}} = \frac{1}{1+\sum_{l\neq k}\exp\{\gamma_i(\pi_{t-1}^{l}-\pi_{t-1}^{k})\}} , \tag{2}$$

where $w_{it|t-1}^{k}$ is the weight fund manager i puts on strategy k at time t that is conditional on time t – 1 information, and γ_i is the intensity of choice parameter, which captures the manager's sensitivity to the past profits of different investment styles and determines the aggressiveness by which he/she switches between different investment styles. For instance, if $\gamma_i = 0$, the fund manager does not respond to differences in relative profitability and does not switch; in this case,

[11] Barberis and Shleifer (2003) employ a process to capture the memory of investors. We apply a discrete measure following Blackburn et al. (2011).

$w^k_{it|t-1} = w^k$. At the other extreme, if $|\gamma_i| \rightarrow \infty$, the fund manager will fully allocate her or his investments to the style that has had the highest comparative performance. For values in between, the fund manager makes partial adjustments in the allocation to specific styles. A positive value for γ_i indicates that the fund manager puts more weight on styles that have performed relatively well in the recent past and therefore behaves as a positive-feedback (momentum) trader. A negative value for γ_i indicates that the fund manager acts as a negative-feedback (contrarian) trader.[12]

The switching rule defined in Equation (2) has several (empirical) advantages.[13] First, it ensures that weights add up to unity. In other words, if a certain style performs better than another, capital is added to the former at the expense of the latter. This is consistent with Barberis and Shleifer (2003), who suggest that switching between styles is self-financed within a specific asset class, and is appropriate for our sample of domestic equity funds, which are almost fully invested in equity and take only long positions.[14] Second, the multinomial switching rule guarantees that each weight is bounded between zero and one, which implies that fund managers cannot switch from a long to a short position and vice versa. This is a reasonable assumption because we are examining US domestic equity funds, which are only allowed to enter into long positions.

[12]See also Goetzmann and Massa (2002) and Blackburn et al. (2011), who use a similar definition of momentum and contrarian traders to identify both types of traders among individual investors.
[13]Technically, this setup is closely related to the 'smooth transition' literature in time-series econometrics; see Van Dijk et al. (2002) for an overview.
[14]The median fund in the sample invests 98% of the portfolio in domestic equity, and the remainder in cash.

The setup is flexible enough to incorporate any t-1 decision variable that might induce managers to adjust exposures, such as other funds' exposures (herding) or their own returns relative to the benchmark (tournament behavior). In this paper, we use lagged style returns that measure momentum and contrarian investing, which follows the model of Barberis and Shleifer (2003). This specification only consumes one additional degree of freedom, whereas the alternatives typically consume one additional degree of freedom per style (see e.g., Swinkels and Tjong-a-Tjoe, 2007). Furthermore, the switching function allows for a change in exposure at each point in time. This would not be possible using rolling regressions, for example, because in such an empirical strategy each beta is estimated over a certain sample period with a minimum number of observations.

Based on the stated investment style of the fund and the past performance of all styles, the fund manager allocates capital. The return of the fund may be explained by the returns on its different styles and the exposures the fund manager has to each investment style, i.e.,

$$r_{it} = \alpha_i + \sum_{k=1}^{K} w_{it|t-1}^{k} \beta_i^k r_t^k + \varepsilon_{it}, \tag{3}$$

where r_{it} is the return of funds i at time t, α_i captures the outperformance or underperformance of the investment styles, and β_i^k captures the unconditional exposure to each investment style k. We include unconditional exposures in this equation because fund managers typically classify themselves as employing a particular investment style. For example, if a fund classifies itself as a growth fund, we expect that there will be an unconditionally greater exposure to the growth investment style than to other styles. Including β_i^k in Equation (3) allows a fund to assume an unconditional exposure to its stated investment style, whereas $w^k_{it|t-1}$ allows for deviations from these unconditional exposures and introduces time-variation into the conditional exposures.

3. Data

We estimate the model presented in Section 2 using data from the CRSP Mutual Fund Database. This is a survivorship-bias-free database that contains monthly mutual fund data from 1961 onwards. Our data run from December 1961 to September 2010. We collect data for US retail funds with more than 10mln USD assets under management that focus on domestic equity and exclude Index-tracking funds. We remove funds with fewer than 36 observations to ensure that we obtain only meaningful estimates for our coefficients. Before estimating the model, we classify funds into investment styles based on the Lipper classification code. We focus on the following twelve styles: large-cap value equity (LCVE), large-cap core equity (LCCE), large-cap growth equity (LCGE), multi-cap value equity (MLVE), multi-cap core equity (MLCE), multi-cap growth equity (MLGE), mid-cap value equity (MCVE), mid-cap core equity (MCCE), mid-cap growth equity (MCGE), small-cap value equity (SCVE), small-cap core equity (SCCE), and small-cap growth equity (SCGE). Next, we check whether a fund's investment style is consistent with its Lipper classification by following Annaert and van Campenhout (2007). For each fund, we estimate a regression of the fund's excess returns on the excess returns of the market, the SMB factor and the HML factor.[15] For this regression, we require the R^2 to be at least 50% and the factor loadings to be consistent with the fund style (i.e., positive exposure to excess market return, and a positive loading on SMB if the fund classifies itself as small cap, a negative loading

[15] We use the data provided on Kenneth French's website.

if it classifies itself as large cap, etc.). Thus, our sample set is composed of 2,044 unique US domestic equity funds.[16]

INSERT TABLE 1 HERE

In Table 1, we report summary statistics for the mutual funds in our sample. All fund types are well represented; mid-cap value equity has the fewest funds in the sample (96), and multi-cap core equity has the greatest number of funds in the sample (326). The median average return shows considerable variation over the various investment styles; large-cap growth equity has the lowest average return per month, of 0.530% (approximately 6.5% per annum), and small-cap core equity has the highest average return of 1.024% per month (approximately 13% per annum). The pattern in returns clearly reveals the presence of a size effect, where small-cap funds generally outperform large-cap funds. The growth effect is less pronounced in this table; two of the size classes (large- and mid-cap) value outperform growth, whereas it is reversed for the other two size classes. The standard deviations also show considerable variation over different investment styles, and we generally find that investment styles with higher risk also yield higher average returns. Minimum and maximum values reveal that returns may vary widely over time; the lowest minimum return is -26.89%, and the highest maximum return is 20.71% per month. These numbers show that there is some negative skewness in our data. The last column shows the median number of observations (months) per fund, which range from 7 to 10 years of data.

[16]We also filter all duplicate funds from our sample. Typically, these are identical funds with different fee structures (A, B, and C funds).

In addition to data on returns, we also obtain data on fund characteristics. We obtain Total Expense Ratio, Fund Age, Total Net Assets, and Turnover from the CRSP mutual fund database.

INSERT TABLE 2 HERE

In Table 2, we report summary statistics on several fund characteristics. The average Total Expense Ratio (TER) for all funds in the sample is 1.41%. In general, we observe that growth funds have higher TERs than value funds (which is consistent with Carhart, 1997) and that small cap funds charge higher TERs than large caps (which is consistent with Brown et al., 2011). The average age of the funds in our sample is 14.24 years, but there is variation across different fund styles. First, we note that core equity funds tend to be younger than value or growth funds. Second, we note that small-cap funds tend to be younger than large-cap funds. The average size of the funds in our sample is $418.5 million, although there is considerable variation in the size of the funds. In general, large-cap funds tend to be larger than small-cap funds. In addition, large-cap value funds tend to be smaller than large-cap growth funds, whereas small-cap value funds tend to be larger than small-cap growth funds. With respect to value and growth funds, we note that growth funds are larger in the large-cap funds, and that value funds are larger for the small-cap funds. With respect to Turnover, we find an average Turnover ratio of 83.30%, which is also broadly consistent with the ratios presented by Carhart (1997) and Brown et al. (2011). Consistent with these studies, we also find variation in Turnover ratio by style; growth funds have higher Turnover ratios than value funds, and small-cap funds have higher Turnover ratios than large-cap funds. These summary statistics suggest that the sample used in our paper has properties similar to those of the samples used by Carhart (1997) and Brown et al. (2011).

To examine the style-switching behavior of mutual fund managers, we relate the performance of each mutual fund to the performance of benchmark portfolios. These benchmark portfolios are obtained from Kenneth French's data library.[17] Instead of using the typical style factors, such as *SMB* and *HML*, we employ the individual portfolios to construct these factors as our investment styles. In particular, we use the large-value (LV), large-growth (LG), small-value (SV), and small-growth (SG) portfolios.[18]

INSERT TABLE 3 HERE

In Panel A of Table 3, we present descriptive statistics about benchmark portfolios. The mean returns show some variation across the different styles, which is consistent with the literature (e.g., Fama and French, 1993). The highest return is observed for the SV benchmark portfolio, with an average return of 1.424% per month, whereas the lowest return is observed for the LG portfolio, with an average return of 0.816% per month. We observe that the value effect in returns is more prominent in small-cap portfolios than in large-cap portfolios. Standard deviations also differ considerably across the benchmark portfolios; the highest standard deviation is observed for the SG portfolio (which has the second lowest average return), and the lowest is observed for the LV portfolio. We also find some notable differences in the skewness

[17]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[18]For more details on the construction of these portfolios, see Kenneth French's website.

of the different benchmark portfolios; large-cap funds have more negatively skewed returns than small-cap funds, and value firms have more negatively skewed returns than growth firms.

In Panel B, we report the correlations between the different benchmark portfolios. Because the benchmark portfolios are not long-short strategies that are market risk neutral, such as SMB and HML, the correlations are high – but not so high that they will cause multicollinearity issues. The highest correlation is between the SV and SG portfolios (0.8838), and the lowest is between the SG and LV portfolios (0.7117).

4. Style and Style-based Feedback Trading

In this section, we present the results of the model from Section 2. We start by presenting results for a specification with constant style exposures. Next, we report the results for two models in which fund managers can either 1) switch between all four styles (e.g., financing investments in growth stocks by selling small-cap stocks), or 2) switch between "twin styles", i.e., between value-growth and large-small separately. We then examine whether the switching behavior of fund managers is related to fund characteristics, and whether style-switching behavior affects the risk-adjusted performance of mutual funds.

4.1 Unconditional Fund Exposures

To examine whether funds follow their stated investment style, we run a regression of the excess returns of a fund on the different investment styles, i.e.,

$$r_{it} = \alpha_i + \beta_i^{SV} r_t^{SV} + \beta_i^{SG} r_t^{SG} + \beta_i^{LV} r_t^{LV} + \beta_i^{LG} r_t^{LG} + \varepsilon_{it}, \tag{4}$$

where $r_t^{SV}, r_t^{SG}, r_t^{LV}, r_t^{LG}$ are the returns on the small-value, small-growth, large-value and large-growth portfolios, respectively. We run this regression for each individual mutual fund.

INSERT FIGURE 1 HERE

In Figure 1, we plot the unconditional loadings on the different investment styles. This plot clearly shows the emergence of two patterns. First, we observe that the loadings on LV and SV decrease when moving from value to core to growth, whereas the loadings on LG and SG increase. This suggests that different investment styles indeed capture the value-growth classification of the funds. Second, when moving from large- to multi- to mid- to small-cap, we observe that the loadings on LV and LG decrease, whereas the loadings on SV and SG increase. This also suggests that different investment styles capture the size classification of the funds. The findings in Figure 1 suggest that funds behave unconditionally according to their stated investment style.

4.2 Style-based Feedback Trading of Fund Managers

To examine whether fund managers engage in style-based feedback trading and switch between investment styles, we estimate the model described in Section 2. Empirically, we do this in two ways. We first estimate a model in which fund managers can switch between all styles and could, for example, increase their exposure to the LG style by lowering their exposure to the SV style. We refer to this as single switching. Second, we estimate a model in which switching occurs according to "twin-styles" (see Barberis and Shleifer, 2003), i.e., fund managers can switch within the value-growth dimension and within the small-large dimension. We refer to this as double switching.

For the single-switching model, we estimate the following equation,

$$r_{it} = \alpha_i + w_{it|t-1}^{SV} \beta_i^{SV} r_t^{SV} + w_{it|t-1}^{SG} \beta_i^{SG} r_t^{SG} + w_{it|t-1}^{LV} \beta_i^{LV} r_t^{LV} + w_{it|t-1}^{LG} \beta_i^{LG} r_t^{LG} + \varepsilon_{it}, \qquad (5)$$

where the weights are computed according to Equation (2) and profits are computed as

$$\pi_{kt-1}^{SV} = \sum_{j=1}^{J} SV_{t-j}, \; \pi_{kt-1}^{SG} = \sum_{j=1}^{J} SG_{t-j}, \; \pi_{kt-1}^{LV} = \sum_{j=1}^{J} LV_{t-j}, \; \pi_{kt-1}^{LG} = \sum_{j=1}^{J} LG_{t-j}\,. \qquad (6)$$

The model defined by Equations (5) and (6) assumes that fund managers switch between the four different strategies mentioned above.

To examine the relevance and existence of twin styles, we further estimate a double switching model, in which we allow the switching to occur over size and/or book-to-market, i.e.,

$$\begin{aligned} r_{it} &= \alpha_i + w_{it|t-1}^{SIZE} w_{it|t-1}^{BM} \beta_{1i} SV_t + w_{it|t-1}^{SIZE} (1 - w_{it|t-1}^{BM}) \beta_{2i} SG_t + \\ &(1 - w_{it|t-1}^{SIZE}) w_{it|t-1}^{BM} \beta_{3i} LV_t + (1 - w_{it|t-1}^{SIZE})(1 - w_{it|t-1}^{BM}) \beta_{4i} LG_t + \varepsilon_{it}, \end{aligned} \qquad (7)$$

where $w_{it|t-1}^{SIZE}$ is the conditional weight on the small-cap style and $w_{it|t-1}^{BM}$ is the conditional weight on the value style. These weights are based on the profitability of each style, measured as

$$
\begin{aligned}
\pi_{kt\text{-}1}^{LARGE} &= \sum_{j_1=1}^{J_1} LV_{t\text{-}j_1} + LG_{t\text{-}j_1} \\
\pi_{kt\text{-}1}^{SMALL} &= \sum_{j_1=1}^{J_1} SV_{t\text{-}j_1} + SG_{t\text{-}j_1} \\
\pi_{kt\text{-}1}^{VALUE} &= \sum_{j_2=1}^{J_2} LV_{t\text{-}j_2} + SV_{t\text{-}j_2} \\
\pi_{kt\text{-}1}^{GROWTH} &= \sum_{j_2=1}^{J_2} LG_{t\text{-}j_2} + SG_{t\text{-}j_2}
\end{aligned}
\quad , \qquad (8)
$$

where $\pi_{kt\text{-}1}^{LARGE}$, π_{kt-1}^{SMALL}, π_{kt-1}^{VALUE} and π_{kt-1}^{GROWTH} are the profitability of the large-cap, small-cap, value, and growth investment styles, respectively. The weights are computed according to Equation (2); however, because Equation (7) has two different weights, we also estimate two intensity of choice parameters (γ^{SIZE} and γ^{BM}). We estimate Equation (7) in three ways. First, we set γ^{SIZE} equal to 0 (this allows for switching in the value-growth dimension only). Second, we set γ^{BM} equal to 0 (this allows for switching in the size dimension only). Finally, we allow for switching in both directions simultaneously.

In Equations (6) and (8), we select the optimal lag length in the profit function by estimating the Equations for j = 1 to 12; we choose the optimal value, j^*, by selecting the specification with the highest log-likelihood.[19] We estimate the switching models introduced in Section 2 for all funds in our sample. However, before presenting the cross-sectional results for all funds, we first examine one specific fund in detail to illustrate the dynamics that the model can generate.

[19]We consider all possible 144 combinations between j_1 and j_2 to find the optimal specification.

4.2.1 The Case of the Oppenheimer Main Street Opportunity Fund

To provide information about and a sense of the underlying dynamics generated by our model, we present detailed results for the Oppenheimer Main Street Opportunity Fund, CRSP fund number 23076. The fund is classified as multi-cap core-equity with data from September 2000 to the end of our sample in September 2010, which yields 120 monthly observations. At the end of the sample period, the fund had $11.6mln assets under management; it is a relatively small fund. From the group of funds that have significant switching parameters, it is a random choice.

INSERT TABLE 4 HERE

Table 4 presents the results for the Oppenheimer fund for the static, the single-switching, the value and size twin styles and the double "twin styles" switching models. The estimates for the static model reveal that the fund has significant exposures to the LG and SV portfolios, and, to a lesser extent, the SG portfolio. Both the multi-cap and the core-equity character are therefore well represented in this fund. To interpret the magnitude of the β's, we must divide the estimated values by four because $\gamma = 0$ in the static model, which gives each weight a value of 0.25. Therefore, a 1% return in the LG portfolio results in, on average, 1.574/4 = 0.3935% return to the fund.

The second column of Table 4 presents the estimation results for the single-switching model (Equations (5) and (6)). The results for the β's remain roughly identical, although β^{SG} becomes insignificant in this model. Most importantly, the intensity of choice parameter, γ, is positive and significant. A Likelihood Ratio test (LR^{STATIC}) confirms that the fit of the switching model is significantly better than the static model.[20] The fact that γ is positive suggests that the manager of the Oppenheimer Main Street Fund follows a positive-feedback (momentum) strategy. In the best fitting model, the manager ranks the performance of the four benchmark portfolios over the past 12 months, $j^* = 12$, and allocates capital in accordance with this ranking.

In the next three columns of Table 4, we present the results for the double-switching models (Equations (7) and (8)). The estimated unconditional exposures are relatively unchanged compared to the static model. For the model in which we only allow for switching in the value-growth dimension, we find a positive and significant coefficient, which indicates that the fund manager acts as a positive-feedback trader. The significance is confirmed by the Likelihood Ratio (LR) test versus the static model, which produces a LR statistic of 5.52. For switching in the size dimension, however, we find an insignificant coefficient, and the LR statistic of 1.78 is also insignificant. This suggests that this fund does not engage in switching behavior in the size dimension. In the last column, we include the double twin-style model, in which switching may occur in both directions. We again observe that γ^{BM} is significant and γ^{SIZE} is not. The twin-style model performs significantly better than the static model, with a LR statistic of 8.10. Finally, we report the LR statistics for the double twin-style model versus the value- and size-twin-style models. The tests show that the double-twin-style model does not improve on the value-twin-style model significantly but does improve on the size-twin-style model significantly. Thus, this

[20]Note that because of the nonlinearity in the model, a t-test may not always indicate whether there is significant evidence for switching. However, a significant increase in likelihood provides this evidence.

fund only displays switching behavior in the value-growth dimension and follows a positive-feedback-trading rule.

INSERT FIGURE 2 HERE

In Figure 2, we plot the relationship between the performance difference for book-to-market and size (π^{VALUE}- π^{GROWTH} and π^{LARGE}- π^{SMALL}) versus the weight put on value and large-cap stocks (w^{VALUE} and w^{LARGE}) for the double-switching model. For both relationships, we observe an upward sloping curve because of the positive values for γ^{BM} and γ^{SIZE}, which leads to a positive relationship between past performance and current exposure. The line for the size switching is steeper than for the book-to-market switching because $\gamma^{SIZE} > \gamma^{BM}$. From Figure 2, we can deduce that the manager changes the weight on value from approximately 0.4 to 0.6 if the value benchmark underperforms or outperforms the growth benchmark by 40% over the previous year. In the size dimension, similar large- and small-cap model underperformance or outperformance leads to a change in the weight on the large-cap model from approximately 0.25 to 0.75. The value weights are concentrated in the upper right corner, whereas the size weights are concentrated in the lower left corner, which implies that value stocks outperformed growth stocks and small caps outperformed large caps over this period.

INSERT FIGURE 3 HERE

Figure 3 shows the profit differences and weights in a time-series plot in which the upper part of the graph shows the weights, w^{VALUE} and w^{LARGE}, and the lower part of the graph shows the performance difference (π^{VALUE}- π^{GROWTH} and π^{LARGE}- π^{SMALL}). Clearly, there is substantial time variation in the book-to-market and size weights, which roughly ranges from 0.2 to 0.8. During the years 2001 and 2002, value stocks outperformed growth stocks, which caused the weight on value firms to be high. For the remaining years, the value premium stays slightly positive, causing the average book-to-market weight to be slightly above 0.5. The size premium is close to zero throughout the sample period, except for the peak in 2001, which caused the fund manager to increase the weight on large stocks. In addition, from late 2003 to the middle of 2004, large-cap stocks underperform small-cap stocks, which decrease the weight on large-cap stocks to its low of approximately 0.2.

INSERT FIGURE 4 HERE

Figure 4 presents a time-series plot of the conditional exposures to the four benchmark portfolios given by the time-varying weights w_{it} multiplied by the unconditional exposures β_i^k. The top-left plot shows the conditional beta on the large-value portfolio. As observed in Table 3, the unconditional exposure to the LV portfolio was small; although there is some variation in the conditional beta, the exposure remains low in absolute terms. The top-right plot shows the conditional beta for the LG portfolio. The unconditional loading on this portfolio was largest, and this portfolio also has the largest absolute variation. Over time, the exposure to LG ranges from a low of approximately 0.25 in late 2001-early 2002 and again in early 2004 to a high of 0.9 near the beginning of 2008. This suggests that there are substantial shifts in the exposure of this fund to the LG portfolio. The bottom-left plot shows the conditional beta of the SV portfolio. There is again considerable variation in the conditional exposure, with exposure peaking from the middle of 2001 to the middle of 2002 and bottoming out at the beginning of 2008. Finally, the bottom-right plot shows the conditional exposure to the SG portfolio. The conditional exposure to the SG portfolio is at its minimum at the beginning of 2001 and peaks in the period 2003-2004. This plot shows also considerable time variation in the conditional exposure to the SG portfolio.

4.2.2 Style-based Feedback Trading in US Domestic Equity Funds

We estimate the single- and twin-style-switching models for all mutual funds in our sample and present summary statistics in Table 5. We first report the percentage of funds for which the likelihood of the single γ model increases significantly at the 5% level compared with the static model (Panel A). We report the percentages of funds with positive and significant γ and with negative and significant γ. In general, we find considerable improvements in model fit when we allow for switching behavior in fund managers. We find that there is significant switching for approximately 53% (30% + 23%) of the funds in our sample. The most significance in switching is reported for the Mid-Cap Value Equity funds (68%), whereas the least significance is found for the Large-Cap Growth Equity funds (44%). This suggests that many fund managers engage in style-based feedback trading.

INSERT TABLE 5 HERE

We split out the percentage of significant switching into positive significant switching (i.e., in which we observe significant positive-feedback or momentum trading) and negative switching (in which we observe significant negative-feedback or contrarian trading). The results reveal several interesting patterns. For all size groups, we observe a clear trend with more positive-feedback (momentum) trading for growth funds and more negative-feedback (contrarian) trading for value funds. This suggests that the type of feedback strategy followed is style dependent. This finding is notable in light of the results reported in Blackburn et al. (2013), who find that individual investors follow positive-feedback strategies when buying growth funds but negative-feedback strategies when buying value funds, which suggests that individual investors follow different strategies for different styles. Our results suggest that this trading behavior extends to mutual fund managers, in addition to being observed in individual investors.

In Panel B of Table 5, we present the results for the twin-style-switching model, in which we allow for two separate switching parameters. This panel presents the percentage of funds for which the double-switching model yields a significantly higher likelihood than the static model. In total, we find significant switching for approximately 77% of the funds in the sample. Although this may seem like a high percentage, this number is consistent with Grinblatt et al. (1995), who find that 77% of funds display return chasing behavior.

We observe several patterns when examining the difference between positive- and negative-feedback trading. For switching in the size dimension, there is more positive-feedback trading for growth funds than for value funds (except for large-cap funds) and more negative-feedback trading for value funds than for growth funds. For switching in the value dimension, we find that there is more positive-feedback trading for growth funds across all size styles and more negative-feedback trading in value funds than in growth funds.

In Panel B3 of Table 5, we report results on single- versus double-twin-style switching. The first row in this panel reports the percentage of funds for which the value-twin-style switching model is best. Most of the funds that switch do so in both the value-growth dimension and the size dimension instead of in one direction only. Growth funds engage more often in double switching than do value funds. In the majority of cases, funds are notably not consistent in their choice of applying positive- or negative-feedback trading with respect to BM and size switching, which is consistent with the findings of Blackburn et al. (2013), who conclude that positive- or negative-feedback trading is not a character trait of investors but is determined by the style in which they are investing.

5. Style–based Feedback Trading and Fund Characteristics

Section 4.2 provides strong evidence of style-based feedback trading behavior in mutual fund managers. In this section, we examine whether this feedback-trading behavior is related to fund characteristics.

INSERT TABLE 6 HERE

Table 6 presents the univariate results in which we sort funds on the estimated γ and create decile portfolios. The first column displays the wide variety of switching tendencies in fund managers, which differs significantly between the top and bottom deciles. The look-back period (lag) increases monotonically over the deciles, indicating that funds that switch more aggressively have a shorter lookback period $j*$. All the performance measures indicate a hump-shaped pattern, with the worst performance for deciles three and four; otherwise, performance appears to improve for funds that switch less. The funds that switch more aggressively charge a significantly higher TER and are younger. The management fee appears to display a similar hump-shaped pattern as the performance measures, with the highest fees for deciles three and four. Turnover is higher with more aggressive switching, confirming our measure of style switching. Finally, TNA is lower for funds that switch more aggressively[21]. These results are consistent over the different measures for switching.

As a more rigorous examination of the relations between fund characteristics and style-based feedback trading, we run a cross-sectional regression of the absolute style-switching parameters on several fund characteristics, i.e.,

$$|\gamma_i| = \beta_1 Log(Age_i) + \beta_2 Log(TNA_i) + \beta_3 Turnover_i + \beta_4 TER_i + \beta_5 Lag + StyleDummy_i + \varepsilon_i, \quad (9)$$

where $Log(Age_i)$ is the log of the median age of the fund, $Log(TNA_i)$ is the log of the beginning of period size of the fund,[22] $Turnover_i$ is the median share turnover of the fund, TER_i is the total expense ratio of the fund, Lag_i is the look-back period j^* that is used to estimate γ, and $StyleDummy_i$ are dummy variables to control for the style of fund i.

[21]The second decile results are affected by a single extremely large fund.

[22]Note that we include beginning of period Total Net Assets of the funds instead of average fund size to avoid endogeneity problems.

In Table 7, we present the results for Equation (9) using the different γ's (i.e., $|\gamma^{SINGLE}|$, $|\gamma^{BM}|$ and $|\gamma^{SIZE}|$) and report White-corrected t-statistics in parentheses.[23] The first column of Table 7 shows the results for $|\gamma^{SINGLE}|$, in which we find a positive and significant relationship with TER, suggesting that funds that switch more charge higher expense ratios. We further find a negative and significant relationship with age, which suggests that older funds tend to switch less aggressively. There is also a negative and significant relationship with *Lag*, which suggests that more aggressive switching occurs with shorter look-back periods.

In the next two columns of Table 7, we separate $|\gamma^{SINGLE}|$ into positive and negative values. We do this to assess whether positive- or negative-feedback trading is affected by specific fund characteristics. We first note that when we split $|\gamma^{SINGLE}|$ into positive and negative, TER is no longer significant for the positive-feedback traders, but remains significant for negative-feedback traders. The negative significance of age is consistent for both positive- and negative-feedback trading. We further observe a positive and significant relationship between positive-feedback trading and turnover and an insignificant relationship between negative-feedback trading and turnover. This suggests that funds that engage in positive-feedback trading trade more actively than negative-feedback traders. Finally, we find that the significant relationship between switching behavior and lag observed in the first column is driven by the negative-feedback trading funds. Negative-feedback traders switch more aggressively based on shorter look-back periods.

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[23]We report the results for all funds in the sample. We have also run this regression only for funds with significant switching with results that are almost identical to those reported in this paper.

INSERT TABLE 7 HERE

In the next set of columns, we report the results for $|\gamma^{BM}|$. The first column in this block shows that switching in the value-growth dimension is positively related to TER. We further observe significantly negative relationships with Age and Lag. When splitting the switching parameter into positive- and negative-feedback trading, TER is only related to positive-feedback trading. The negative relationships of $|\gamma^{BM}|$ with age and lag are observed in both positive- and negative-feedback trading.

The last block of columns from Table 7 reports the regression results for $|\gamma^{SIZE}|$. In the first column, we observe that $|\gamma^{SIZE}|$ has a negative and significant relationship with Age, i.e., older funds switch less aggressively in the size dimension. We further find a significant positive relationship with Turnover, which suggests that funds that switch more aggressively in the size dimension have a higher turnover of stocks in their portfolio. When splitting $|\gamma^{SIZE}|$ into positive- and negative-feedback trading, we find that the relationship between $|\gamma^{SIZE}|$ and Age is driven by negative-feedback-trading funds, i.e., older funds engage in less negative-feedback trading (there is no significant relationship between positive-feedback trading and age). The relationship between turnover and $|\gamma^{SIZE}|$ is driven by the positive-feedback trading funds. We further find a significantly negative relationship between Lag and positive-feedback-trading in the size dimension, suggesting that fund managers that follow a momentum strategy in the size dimension trade more aggressively with shorter look-back periods.

6. Style-based Feedback Trading, Outperformance, and Fund Flows

The next issue we address is whether the style-based feedback-trading behavior of fund managers is related to the outperformance. To address this question, we compute Jensen's α for each mutual fund and use these α's in the following cross-sectional regression,

$$\begin{aligned} \alpha_i &= c + \beta_1 \gamma_i^+ + \beta_2 \gamma_i^+ * Lag_i + \beta_3 \gamma_i^- + \beta_4 \gamma_i^- * Lag_i + \beta_5 Lag_i \\ &+ FundControls_i + StyleDummy_i + \varepsilon_i \end{aligned} \tag{10}$$

where α_i is the outperformance measure, for which we take the CAPM-alpha, Fama-French 3-factor alpha, and the 4-factor alpha; and γ_i^+ and γ_i^- are the style-switching parameters for positive-feedback trading and negative-feedback trading, respectively. We include an interaction term between γ and *Lag* (j^*) because different trading strategies may work better for different look-back periods, i.e., positive-feedback (momentum) trading may work better if it is based on switching rules that look back for only a few months (in which case Lag is low), whereas negative-feedback (contrarian) trading, may work better if the look-back period is longer (in which case Lag is high). $FundControls_i$ account for different fund characteristics known from the literature that may lead to outperformance, and $StyleDummy_i$ are dummy variables to control for the investment style of fund *i*.

INSERT TABLE 8 HERE

In Table 8, we report the results for Equation (10). The first columns assess the relationship between the single-switching parameter and the risk-adjusted performance of a fund and show that positive-feedback trading yields outperformance. However, the coefficient on the interaction term of positive-feedback trading and the look-back period (Lag) is negative, which suggests that the outperformance obtained from positive-feedback trading decreases as the look-back period increases. These results hold for all measures of outperformance and are consistent with those of Grinblatt et al. (1995), who find that momentum investing at the stock level yields significantly higher performance.

The effect of negative-feedback trading has the opposite pattern; it causes loss in the short-run because of the positive significant coefficient for γ^{-}. For longer lags, the negative effect decreases, although not so significantly.

For fund-level control variables, we find a negative relationship between α and Age, Fund Size, and Turnover; we find a negative relationship between α and TER. These results are consistent with the literature (see e.g. Carhart, 1997).

In columns 2 and 3, we report the results for the switching in the B/M and size dimensions, respectively. For style-switching in the B/M dimension, we find insignificant results for the positive-feedback-trading rules, whereas we find a significantly negative relationship between risk-adjusted performance and the negative-feedback-trading rules. For the size dimension, we find that a longer look-back period leads to higher performance, irrespective of the sign of feedback trading. A striking difference in the results of the switch alpha is that negative-feedback trading does yield outperformance at short lags, which decreases as the number of lags increases; otherwise, the results are qualitatively similar for different measures of outperformance.

The next question is whether fund managers engage in style-based feedback trading to attract fund flows. Barberis and Shleifer (2003) argue that fund managers might chase style returns because of agency considerations, as it is an investment strategy that is relatively easy to sell to (retail) investors. To test for this hypothesis, we estimate the following equation,

$$\begin{aligned} Flows_i = c + \beta_1\gamma_i^+ + \beta_2\gamma_i^+ * Lag_i + \beta_3\gamma_i^- + \beta_4\gamma_i^- * Lag_i + \beta_5 Lag_i \\ + FundControls_i + StyleDummy_i + \varepsilon_i \end{aligned} \quad (11)$$

in which $Flows_i$ is the median net-inflow into fund i.

INSERT TABLE 9 HERE

The results for Equation (11) are shown in Table 9, which show that there is no particular relationship between switching and fund flows. For certain γ-Lag combinations, we find marginal significance, but it is not consistent across measures for style switching, and the sign varies. Thus, we conclude that switching does not affect fund flows. The control variables are consistent with earlier findings in the literature; flow is positively related to performance, whereas flow is inversely related to total expense ratio.

7. Conclusions

This paper seeks empirical evidence for the style-based switching model proposed by Barberis and Shleifer (2003) to connect institutional trader behavior to market returns. Using a sample of US equity funds, we find strong evidence for style-based feedback trading by fund managers. Approximately 77% of the funds in our sample display some form of style-based feedback trading. Slightly more than half of these are negative-feedback traders that increase (decrease) the exposure to recent losers (winners). Switching seems to occur predominantly between the value and growth styles and less between the small- and large-cap styles. A higher propensity to switch is found for funds with a higher total expense ratio, younger funds, value funds, and mid-cap funds. Finally, we find that when fund managers apply feedback-trading rules ‘correctly’ – momentum trading in the short run and contrarian trading in the long run – they achieve extra gains. However, fund managers applying these rules ‘incorrectly’, such as long-term momentum and short-term contrarian trading, may exhibit underperformance. In general, the assumptions about the behavior of institutional investors and the relation of their behavior to market returns, as put forward by Barberis and Shleifer (2003), is confirmed.

References

Annaert, J. and van Campenhout, G., 2007. Time variation in mutual fund style exposures. *Review of Finance* 11, 633-661.

Bange, M.M., 2000. Do the portfolios of small investors reflect positive feedback trading? *Journal of Financial and Quantitative Analysis* 35, 239–255.

Barberis, N., Shleifer, A., 2003. Style investing. *Journal of Financial Economics* 68, 161-199.

Blackburn, D., Goetzman, W. and Ukhov, A., 2013. Is trading behavior stable across contexts? Evidence from style and multi-style investors. *Quantitative Finance*, Forthcoming.

Brock, W. A. and Hommes, C. H., 1997. A rational route to randomness. *Econometrica* 65, 1059-1095.

Brock, W. A. and Hommes, C. H., 1998. Heterogeneous beliefs and routes to chaos in a simple asset pricing model. *Journal of Economic Dynamics and Control* 22, 1235-1274.

Brown, K. Harlow, W., and Starks, L., 1996. Of tournaments and temptations: an analysis of managerial incentives in the mutual fund industry. *Journal of Finance* 51, 85-110.

Brown, K., Harlow, W., and Zhang, H., 2011. Investment style volatility and mutual fund performance. *Working paper*.

Budiono, D. and Martens, M, 2010. Mutual fund style timing skills and alpha. *Working paper*.

Carhart, M.M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52, 57-82.

Chan, L. K. Chen, H.-L. and Lakonishok, J., 2002. On mutual fund investment styles. *Review of Financial Studies* 15, 1407-1437.

Chevalier, J., and Ellison, G., 1997. Risk Taking by Mutual Funds as a Response to Incentives. *Journal of Political Economy* 105, 1167-1200.

Choe, H., Kho, B.C. and R. Stulz, 1999. Do foreign investors destabilize stock markets? *Journal of Financial Economics* 54, 227–264.

Cooper, M.J., Gulen, H., and Rau, P.R., 2005. Changing Names with Style: Mutual Fund Name Changes and Their Effects on Fund Flows. *Journal of Finance* 60, 2825-2858.

Van Dijk, D., T. Teräsvirta and P.H. Franses, 2002. Smooth Transition Autoregressive Models – A Survey of Recent Developments, *Econometric Reviews* 21: 1-47.

Fama, E.F. and K.R. French, 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3-56.

Froot, K., O'Connell, P. and M. Seasholes, 2001. The portfolio flows of international investors. *Journal of Financial Economics* 59, 149–193.

Froot, K. and Teo, M., 2008. Style investing and institutional investors. *Journal of Financial and Quantitative Analysis* 43, 883-906.

Goetzman, W. and Massa, M., 2002. Daily momentum and contrarian behaviour of index fund investors. *Journal of Financial and Quantitative Analysis* 37, 375-389.

Gompers, P. and Metrick, A., 2001. Institutional Investors and Equity Prices. *Quarterly Journal of Economics* 116, 229-259.

Grinblatt, M., Titman, S., and Wermers, R. (1995). Momentum Investment Strategies, Portfolio Performance, and Herding: A Study of Mutual Fund Behavior, *American Economic Review* 85, 1088-1105.

Jegadeesh, N. and S. Titman, 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance* 48, 65-91.

Keim, D.B. and A. Madhavan, 1995. Anatomy of the trading process: Empirical evidence on the behavior of institutional investors. *Journal of Financial Economics* 37, 371–398.

Manski, C. F. and McFadden, D., 1981. *Structural analysis of discrete data with econometric applications*. MIT Press, Cambridge, MA.

Pomorski, L., 2004. Style Investing: Evidence from Mutual Fund Flows, *working paper, University of Toronto*.

Rouwenhorst, K.G., 1998. International momentum strategies. *Journal of Finance* 53, 267-284.

Sirri, E. and Tufano, P., 1998. Costly search and mutual fund flows. *Journal of Finance* 53, 1589-1662.

Swinkels, L., and Tjong-a-Tjoe, L., 2007. Can mutual funds time investment styles? *Journal of Asset Management* 8, 123-132.

Teo, M. and Woo, S.-J., 2004. Style effects in the cross-section of stock returns. *Journal of Financial Economics* 74, 367-398.

Wermers, R. (2012). Matter of Style: The Causes and Consequences of Style Drift in Institutional Portfolios, *Working Paper*, University of Maryland.

Table 1. Mutual Fund Descriptive Statistics

	# FUNDS	MEDIANS				
		RETURN	STDEV	MIN	MAX	# OBS
LCVE	128	0.686%	4.860%	-18.108%	9.716%	125
LCCE	208	0.667%	4.931%	-18.049%	9.471%	104.5
LCGE	128	0.530%	5.535%	-19.438%	11.213%	114
MLVE	239	0.663%	4.973%	-19.787%	10.498%	122
MLCE	326	0.731%	5.034%	-18.970%	9.999%	89.5
MLGE	184	0.756%	6.253%	-22.262%	13.280%	124
MCVE	96	0.916%	5.567%	-23.026%	13.138%	112.5
MCCE	120	0.976%	6.041%	-24.471%	13.473%	98
MCGE	145	0.848%	7.225%	-25.184%	17.658%	93
SCVE	163	0.943%	6.006%	-23.089%	13.940%	123
SCCE	168	1.024%	6.462%	-23.409%	14.662%	92
SCGE	139	0.944%	7.536%	-26.892%	20.709%	110

Note: This Table presents descriptive statistics for the mutual funds in the sample. LC, ML, MC, and SC represents large cap, multi cap, mid cap, and small cap, respectively. VE, CE, and GE represents value equity, core equity, and growth equity, respectively. #FUNDS is the total number of funds in each particular style classification. All other variables are presented as median values over all funds. RETURN, STDEV, MIN, and MAX are presented as monthly percentages.

Table 2. Fund Characteristics

	ALL	LCVE	LCCE	LCGE	MLVE	MLCE	MLGE	MCVE	MCCE	MCGE	SCVE	SCCE	SCGE
							Total Expense Ratio						
Mean	1.41%	1.26%	1.32%	1.43%	1.35%	1.25%	1.49%	1.39%	1.39%	1.65%	1.47%	1.45%	1.62%
Std Dev	0.53%	0.51%	0.51%	0.54%	0.49%	0.55%	0.54%	0.42%	0.57%	0.58%	0.43%	0.50%	0.41%
Perc. 5%	0.51%	0.47%	0.56%	0.68%	0.53%	0.20%	0.75%	0.79%	0.40%	0.91%	0.96%	0.57%	1.04%
Perc. 50%	1.35%	1.17%	1.25%	1.30%	1.26%	1.26%	1.45%	1.29%	1.39%	1.55%	1.40%	1.41%	1.50%
Perc. 95%	2.27%	2.08%	2.17%	2.28%	2.17%	2.14%	2.34%	2.15%	2.25%	2.50%	2.37%	2.27%	2.50%
							Fund Age (in years)						
Mean	14.24	16.66	14.03	15.59	15.65	13.14	15.62	15.60	13.35	13.30	14.44	11.31	13.31
Std Dev	10.52	14.56	12.56	11.74	12.19	10.04	12.07	9.26	8.89	9.85	6.73	5.41	6.80
Perc. 5%	5.00	4.91	4.47	4.24	5.22	4.78	4.26	5.42	5.21	5.16	5.29	5.42	5.34
Perc. 50%	11.84	12.76	10.59	12.41	12.75	10.76	13.17	13.62	10.91	10.93	13.63	10.42	12.80
Perc. 95%	32.93	45.95	34.81	41.68	34.39	25.59	43.61	35.42	27.97	33.71	26.04	18.59	25.76
							Total Net Assets (in Millions)						
Mean	418.5	530.2	770.5	858.2	334.4	411.9	444.1	399.3	440.5	168.1	333.0	195.8	170.9
Std Dev	1754.5	1348.2	4394.0	2584.5	766.5	1285.3	1302.1	656.4	1084.6	286.9	941.6	358.3	372.4
Perc. 5%	15.1	16.1	14.2	14.2	15.0	13.8	15.3	18.8	17.2	14.3	16.4	15.9	15.0
Perc. 50%	72.3	88.4	67.8	78.8	83.3	65.4	93.2	132.1	68.5	49.3	64.9	69.8	67.9
Perc. 95%	1598.5	2911.7	2056.7	6338.3	1573.7	2326.7	2243.4	1814.3	2937.0	755.3	1500.3	640.1	663.1
							Turnover (percentage of TNA)						
Mean	83.30%	64.07%	60.40%	80.97%	57.75%	69.66%	123.65%	75.60%	84.37%	126.17%	65.93%	95.35%	120.27%
Std Dev	93.87%	81.84%	43.81%	87.17%	38.76%	77.42%	162.61%	89.03%	82.29%	93.00%	76.41%	133.09%	63.67%
Perc. 5%	11.50%	7.00%	4.00%	16.00%	14.00%	4.50%	21.00%	11.00%	17.00%	28.00%	17.00%	19.00%	46.50%
Perc. 50%	64.00%	51.00%	52.50%	68.48%	47.00%	51.00%	90.50%	62.00%	65.00%	104.00%	53.00%	68.00%	100.25%
Perc. 95%	204.00%	192.00%	139.50%	166.00%	138.00%	204.00%	267.00%	150.00%	230.50%	280.00%	133.50%	195.50%	245.00%

Note: This Table presents summary statistics on fund characteristics. We present the values for the mean, standard deviation, and the 5%, 50%, and 95% percentiles. We report statistics for the Total Expense Ratio, Fund Age, Total Net Assets, and Turnover for all funds and per fund category.

Table 3. Descriptive Statistics for the Benchmark Portfolios

	LV	LG	SV	SG
Panel A: Descriptive Statistics				
Mean	1.073%	0.816%	1.424%	0.827%
Median	1.325%	0.920%	1.760%	1.055%
Maximum	21.090%	21.260%	30.270%	28.880%
Minimum	-22.640%	-23.230%	-27.720%	-32.340%
Std. Dev.	4.720%	4.753%	5.660%	6.969%
Skewness	-0.413	-0.292	-0.377%	-0.303%
Kurtosis	5.604	4.676	6.335	4.671
Panel B: Correlations				
LV	1.0000			
LG	0.7825	1.0000		
SV	0.8512	0.7433	1.0000	
SG	0.7117	0.8259	0.8838	1.0000

Note: This Table presents descriptive statistics for the four benchmark portfolios. SV, SG, LV, and LG, represents small value, small growth, big value, and big growth, respectively.

Table 4. Estimation results for the Oppenheimer Main Street Opportunity Fund

	Static Model	Single γ	Value twin style	Size twin style	Double twin styles
β^{LV}	0.309	0.000	-0.038	0.554	0.129
	(0.913)	(0.002)	(-0.142)	(1.601)	(0.441)
β^{LG}	1.574***	2.253***	2.274***	1.756***	2.510***
	(3.844)	(3.631)	(4.135)	(4.221)	(4.961)
β^{SV}	1.117***	0.975***	1.112***	0.838**	0.824***
	(3.238)	(3.429)	(4.310)	(2.138)	(2.896)
β^{SG}	0.598*	0.605	0.568	0.564*	0.573*
	(1.886)	(1.395)	(1.560)	(1.720)	(1.707)
γ		0.021***			
		(2.779)			
γ^{BM}			0.013***		0.011**
			(2.600)		(2.557)
γ^{SIZE}				0.024	0.025
				(1.201)	(0.020)
α	-0.130	-0.129	-0.194	-0.098	-0.143
	(-0.197)	(-0.450)	(-0.724)	(-0.389)	(-0.555)
Lag		12	12	12	12, 12
LOGL	-254.43	-251.07	-251.67	-253.54	-250.38
LR^{STATIC}		6.720***	5.520**	1.780	8.100***
LR^{BM}					-2.580
LR^{SIZE}					-6.320**

Note: This Table presents the estimation results of the static model (first column); the single switching model (second column); the twin style value switching model (third columns); the twin style size switching model (fourth columns); and the double twin style model (third column) for the Oppenheimer Main Street Opportunity Fund. White corrected t-statistics are reported in parentheses. LR^{STATIC} is the outcome of a Likelihood Ratio test versus the static model. LR^{BM} is the outcome of a Likelihood Ratio test of the twin style value model versus the double twin style model, and LR^{SIZE} is the outcome of a Likelihood Ratio test of the twin style size model versus the double twin style model. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 5. Percentage of Switching Funds

	ALL	LCVE	LCCE	LCGE	MCVE	MCCE	MCGE	MLVE	MLCE	MLGE	SCVE	SCCE	SCGE
							Panel A: Single γ Model						
Total	52.56%	50.45%	47.90%	44.33%	68.67%	50.98%	57.69%	52.15%	52.79%	49.38%	48.46%	50.75%	60.83%
Positive γ	22.61%	12.84%	13.77%	20.62%	18.07%	21.57%	40.77%	11.96%	27.51%	41.36%	2.31%	16.42%	43.33%
Negative γ	29.95%	37.61%	34.13%	23.71%	50.60%	29.41%	16.92%	40.19%	25.28%	8.02%	46.15%	34.33%	17.50%
							Panel B1: Twin Styles – Only BM Switching						
Total	20.69%	20.93%	24.82%	16.67%	24.10%	21.57%	14.62%	28.87%	26.02%	10.69%	11.29%	25.98%	15.13%
Positive γ	5.96%	0.00%	4.26%	5.95%	4.82%	6.86%	8.46%	5.15%	5.69%	5.03%	1.61%	11.02%	11.76%
Negative γ	14.73%	20.93%	20.57%	10.71%	19.28%	14.71%	6.15%	23.71%	20.33%	5.66%	9.68%	14.96%	3.36%
							Panel B2: Twin Styles – Only Size Switching						
Total	17.62%	25.58%	12.06%	8.33%	24.10%	22.55%	13.85%	10.82%	14.23%	19.50%	29.84%	16.54%	24.37%
Positive γ	9.03%	18.60%	6.38%	2.38%	10.84%	11.76%	10.77%	6.19%	7.72%	13.84%	0.81%	7.09%	15.97%
Negative γ	8.59%	6.98%	5.67%	5.95%	13.25%	10.78%	3.08%	4.64%	6.50%	5.66%	29.03%	9.45%	8.40%
							Panel B3: Twin Styles – Double Switching						
Total	38.9%	29.1%	32.6%	38.1%	36.1%	34.3%	54.6%	40.2%	37.0%	43.4%	42.7%	29.1%	44.5%
Pos Size – Pos BM	8.84%	5.81%	5.67%	3.57%	6.02%	4.90%	18.46%	10.82%	7.72%	16.35%	4.03%	3.15%	13.45%
Pos Size – Neg BM	11.10%	12.79%	7.09%	10.71%	7.23%	15.69%	19.23%	10.31%	9.76%	10.06%	6.45%	11.81%	14.29%
Neg Size – Pos BM	9.84%	4.65%	6.38%	11.90%	10.84%	4.90%	13.08%	7.22%	11.38%	8.81%	18.55%	7.09%	12.61%
Neg Size – Neg BM	9.09%	5.81%	13.48%	11.90%	12.05%	8.82%	3.85%	11.86%	8.13%	8.18%	13.71%	7.09%	4.20%
							Panel B4: Twin Styles – TOTAL						
Total	77.2%	75.6%	69.5%	63.1%	84.3%	78.4%	83.1%	79.9%	77.3%	73.6%	83.8%	71.6%	84.0%

Note: This Table presents the percentage of funds for which we find significant switching. Specifically, we give the percentage of funds for which the likelihood ratio test indicates that switching adds significantly to the explanatory power of the model. Panel A represents results of the single switching model versus the static model; Panel B presents the results of the double switching model versus the static model; and Panel C presents the results of the single versus double switching model.

Table 6. Relation between Style Switching and Fund Characteristics

	|γ|	lag	alpha_capm	alpha_ff3	alpha_ff4	TER	Age	mfee	turnover	TNA
Panel A: Single Switching										
High 1	0.095	5.293	-0.333	-0.448	-0.425	0.015	4103	0.732	0.903	31.79
2	0.029	5.266	-0.367	-0.472	-0.427	0.014	5232	0.764	0.876	126.06
3	0.018	5.165	-0.407	-0.484	-0.470	0.015	4976	0.793	1.159	40.55
4	0.013	5.846	-0.413	-0.471	-0.448	0.015	5085	0.770	0.926	26.74
5	0.010	5.963	-0.435	-0.460	-0.444	0.014	4985	0.730	0.904	34.38
6	0.008	5.594	-0.400	-0.402	-0.392	0.015	4836	0.628	0.720	27.20
7	0.006	6.064	-0.347	-0.336	-0.321	0.014	5065	0.673	0.718	41.96
8	0.005	7.367	-0.346	-0.363	-0.322	0.014	5512	0.707	0.771	58.98
9	0.004	7.340	-0.321	-0.344	-0.330	0.014	5101	0.695	0.722	50.98
Low 10	0.002	8.277	-0.327	-0.331	-0.320	0.013	5397	0.685	0.693	52.48
High -/- Low	0.093	-2.984	-0.010	-0.118	-0.105	0.002	-1294	0.047	0.209	-20.69
	(0.000)	(0.000)	(0.869)	(0.001)	(0.001)	(0.000)	(0.000)	(0.170)	(0.028)	(0.089)
Panel B: Double Switching: BM										
High 1	0.144	3.320	-0.440	-0.528	-0.471	0.015	4094	0.761	0.867	30.269
2	0.051	4.580	-0.400	-0.510	-0.451	0.014	5057	0.719	0.780	40.796
3	0.035	4.667	-0.381	-0.484	-0.442	0.014	5345	0.708	0.725	45.864
4	0.025	5.006	-0.364	-0.459	-0.424	0.013	5205	0.696	0.741	33.774
5	0.018	5.685	-0.326	-0.425	-0.400	0.013	5677	0.701	0.791	66.862
6	0.013	6.221	-0.373	-0.439	-0.415	0.014	5215	0.712	0.798	62.925
7	0.009	6.392	-0.374	-0.376	-0.386	0.014	4862	0.675	0.921	46.703
8	0.006	6.894	-0.339	-0.301	-0.307	0.014	5283	0.752	0.884	34.201
9	0.004	6.906	-0.375	-0.327	-0.332	0.014	5802	0.719	0.920	118.80
Low 10	0.002	7.260	-0.277	-0.246	-0.238	0.014	5455	0.724	0.903	37.151
High -/- Low	0.142	-3.939	-0.163	-0.283	-0.234	0.001	-1361	0.037	-0.036	-6.882
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.281)	(0.770)	(0.316)
Panel C: Double Switching: Size										
1	0.193	6.077	-0.319	-0.396	-0.387	0.015	3743	0.738	1.237	26.67
2	0.060	5.680	-0.297	-0.405	-0.385	0.015	4541	0.751	0.908	32.52
3	0.036	6.250	-0.324	-0.398	-0.390	0.015	4913	0.763	0.887	49.91
4	0.025	6.249	-0.392	-0.468	-0.441	0.0150	4776	0.752	0.894	37.31
5	0.018	6.249	-0.399	-0.432	-0.403	0.014	5418	0.787	0.884	41.34
6	0.013	6.674	-0.394	-0.439	-0.410	0.014	6119	0.734	0.791	51.04
7	0.009	6.735	-0.418	-0.436	-0.407	0.014	6238	0.722	0.739	47.30
8	0.007	6.844	-0.365	-0.376	-0.353	0.014	5683	0.697	0.790	59.59
9	0.004	6.834	-0.382	-0.399	-0.367	0.012	5482	0.645	0.671	105.27
10	0.002	7.055	-0.359	-0.347	-0.323	0.012	5082	0.577	0.528	66.57
High -/- Low	0.191	-0.978	0.040	-0.049	-0.065	0.003	-1339	0.161	0.709	-39.90
	(0.000)	(0.015)	(0.312)	(0.209)	(0.069)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)

Note: this table presents the univariate relationship between the intensity of choice γ and several fund characteristics. We sorted funds in deciles portfolios and calculated fund characteristics within the portfolios. High -/- low represents the test of equal means between the first and tenth portfolio; p-values in parentheses.

Table 7. Relation between Style Switching and Fund Characteristics

	Single Switching			Double Switching					
	$\|\gamma^{SINGLE}\|$			$\|\gamma^{BM}\|$			$\|\gamma^{SIZE}\|$		
	All	Pos	Neg	All	Pos	Neg	All	Pos	Neg
TER	0.344**	0.199	0.372**	0.469**	0.785**	0.190	-0.379	-0.422	-0.390
	(2.078)	(0.674)	(2.138)	(2.189)	(2.000)	(0.827)	(-0.882)	(-0.606)	(-0.823)
LOG(AGE)	-0.006***	-0.006**	-0.008***	-0.012***	-0.015***	-0.010***	-0.014***	-0.003	-0.026***
	(-4.939)	(-2.268)	(-4.867)	(-6.480)	(-5.179)	(-4.487)	(-4.498)	(-0.756)	(-6.780)
LOG(TNA)	0.000	-0.002	0.002**	0.000	-0.002	0.001	-0.001	-0.002	0.002
	(0.365)	(-1.541)	(2.098)	(0.289)	(-1.135)	(1.014)	(-1.490)	(-0.896)	(1.062)
TURNOVER	0.001	0.004*	-0.001	0.001	0.002	-0.001	0.006***	0.008***	0.003
	(1.033)	(1.829)	(-1.023)	(0.640)	(0.889)	(-0.568)	(2.945)	(4.247)	(0.628)
LAG	-0.001***	-0.001	-0.001***	-0.003***	-0.004***	-0.003***	-0.001	-0.001**	-0.001
	(-2.843)	(-0.798)	(-5.721)	(-9.143)	(-5.731)	(-5.792)	(-1.490)	(-2.610)	(-1.035)
Style dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2	0.070	0.066	0.135	0.136	0.162	0.108	0.065	0.088	0.085
#OBS	1878	838	1040	1807	796	1011	1807	901	906

Note: this table reports the regression results for Equation (9). $|\gamma^{SINGLE}|$ is the absolute value of the style switching coefficient in the single switching model (Equations (5) and (6)); $|\gamma^{SIZE}|$ and $|\gamma^{BM}|$ are the absolute values of the style switching coefficients in the double switching model (Equations (7) and (8)); $Log(Age_i)$ is the log of the age of the fund; $Log(TNA_i)$ is the log of the beginning of period size of the fund; $Turnover_i$ is the median share turnover of the fund; and TER_i is the total expense ratio of the fund. In each regression, we include dummy variables to control for the stated fund style (not reported). We report White corrected t-statistics in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 8. Risk-Adjusted Performance and Style Switching

	γ^{SINGLE}			γ^{BM}			γ^{SIZE}		
	Alpha CAPM	Alpha FF3	Alpha FF4	Alpha CAPM	Alpha FF3	Alpha FF4	Alpha CAPM	Alpha FF3	Alpha FF4
γ+	0.331*	0.551***	0.442**	-0.109	0.087	0.125	-0.158	0.013	0.184
	(1.867)	(3.212)	(2.458)	(-0.425)	(0.348)	(0.553)	(-0.326)	(0.032)	(0.501)
*γ+*Lag*	-0.011	-0.087***	-0.113***	0.007	-0.042	-0.086*	0.027	-0.014	-0.055
	(-0.410)	(-4.941)	(-6.836)	(0.134)	(-0.728)	(-1.616)	(0.418)	(-0.280)	(-1.028)
γ-	1.442**	1.135*	1.106**	1.419***	1.435***	0.846***	-0.412	-0.566	-0.366
	(2.030)	(1.890)	(2.016)	(2.871)	(3.508)	(2.416)	(-1.061)	(-1.461)	(-1.023)
*γ-*Lag*	-0.034	-0.063	-0.137	0.090	0.009	0.007	0.061	0.062	0.036
	(-0.321)	(-0.651)	(-1.568)	(0.553)	(0.077)	(0.070)	(1.353)	(1.381)	(0.848)
Lag	0.003	0.003	0.003	0.001	0.001	0.001	0.009***	0.008***	0.006***
	(1.490)	(1.451)	(1.322)	(0.530)	(0.350)	(0.366)	(3.164)	(3.693)	(2.831)
Log(Age)	-0.047***	-0.057***	-0.050***	-0.058***	-0.067***	-0.060***	-0.055***	-0.063***	-0.056***
	(-2.690)	(-3.652)	(-3.451)	(-3.201)	(-4.212)	(-4.091)	(-2.991)	(-3.969)	(-3.909)
Log(TNA)	-0.021**	-0.026***	-0.020**	-0.024**	-0.024***	-0.017**	-0.025***	-0.026***	-0.018**
	(-2.244)	(-2.977)	(-2.508)	(-2.570)	(-2.825)	(-2.197)	(-2.681)	(-2.926)	(-2.254)
Turnover	-0.027**	-0.034***	-0.038***	-0.028**	-0.035***	-0.038***	-0.026**	-0.032***	-0.037***
	(-2.171)	(-3.615)	(-3.533)	(-2.289)	(-3.668)	(-3.516)	(-1.985)	(-3.380)	(-3.443)
TER	-9.758***	-8.488***	-7.417***	-10.253***	-8.835***	-7.443***	-10.084***	-8.673***	-7.431***
	(-5.057)	(-5.237)	(-4.818)	(-5.177)	(-5.453)	(-4.814)	(-5.205)	(-5.467)	(-4.930)
Style dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES
R^2(adj)	0.073	0.112	0.091	0.100	0.132	0.088	0.073	0.111	0.082

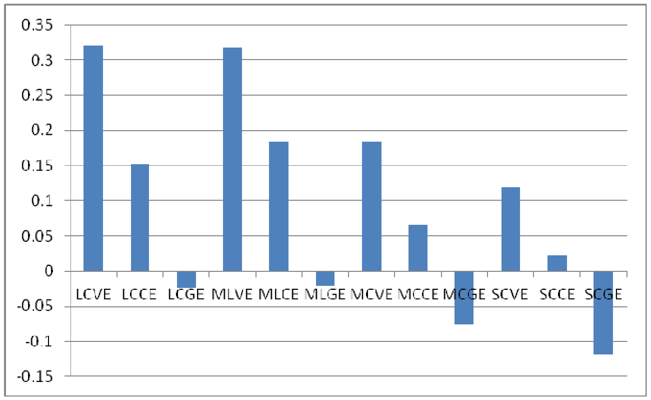
Note: This Table displays the estimation results of Equation (10). γ^{SINGLE} is the style switching coefficient in the single switching model (Equations (5) and (6)); γ^{SIZE} and γ^{BM} are the style switching coefficients in the double switching model (Equations (7) and (8)); γ_i^+ and γ_i^- are the style switching parameters for positive feedback trading and negative feedback trading, respectively. *Lag* is the optimal lookback period j^*; *Log(Age$_i$)* is the log of the age of the fund; *Log(TNA$_i$)* is the log of the beginning of period size of the fund; *Turnover$_i$* is the median share turnover of the fund; and *TER$_i$* is the total expense ratio of the fund. In each regression we include dummy variables to control for the stated fund style (not reported). We report White corrected t-statistics in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

Table 9. Fund Flows and Style Switching

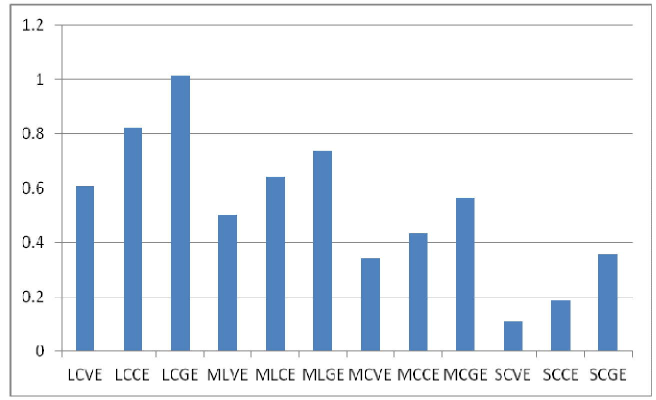
	γ^{SINGLE}	γ^{BM}	γ^{SIZE}
γ+	2.675	-3.547	-0.921
	(0.952)	(-1.077)	(-0.221)
*γ+*Lag*	-0.096	1.138	-0.076
	(-0.340)	(1.253)	(-0.141)
γ-	11.382	6.339	-4.420
	(0.950)	(1.145)	(-1.184)
*γ-*Lag*	-1.164	-0.205	0.937*
	(-0.727)	(-0.260)	(1.944)
Lag	-0.029	-0.105	0.041
	(-0.370)	(-1.602)	(0.632)
Alpha 4FF	2.620***	2.903***	2.911***
	(4.375)	(4.704)	(4.555)
Log(Age)	-0.547	-0.491	-0.493
	(-1.586)	(-1.414)	(-1.415)
Log(TNA)	-0.078	-0.236	-0.254
	(-0.163)	(-0.523)	(-0.565)
Turnover	-0.175	-0.125	-0.113
	(-1.004)	(-0.750)	(-0.682)
TER	-328.88***	-322.59***	-326.68***
	(-4.268)	(-4.443)	(-4.387)
Style dummies	YES	YES	YES
R^2(adj)	0.058	0.059	0.058

Note: This Table displays the estimation results of Equation (11). γ^{SINGLE} is the style switching coefficient in the single switching model (Equations (5) and (6)); γ^{SIZE} and γ^{BM} are the style switching coefficients in the double switching model (Equations (7) and (8)). γ_i^+ and γ_i^- are the style switching parameters for positive feedback trading and negative feedback trading, respectively. *Lag* is the optimal lookback period j^*; *Log(Age$_i$)* is the log of the age of the fund; *Log(TNA$_i$)* is the log of the beginning of period size of the fund; *Turnover$_i$* is the median share turnover of the fund; and *TER$_i$* is the total expense ratio of the fund. In each regression we include dummy variables to control for the stated fund style (not reported). We report White corrected t-statistics in parentheses. We indicate significance at the 10%, 5% and 1% level, by *, **, and ***, respectively.

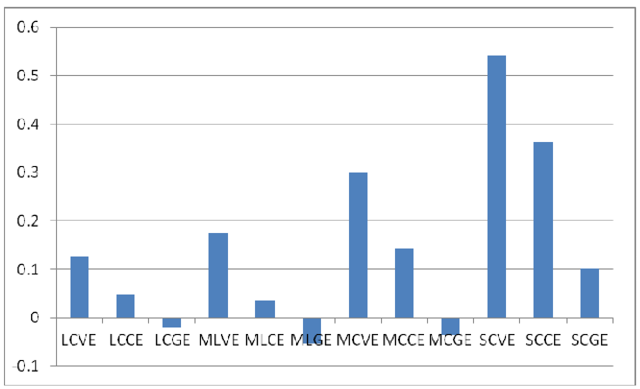
Figure 1. Unconditional Loadings on the Different Investment Styles



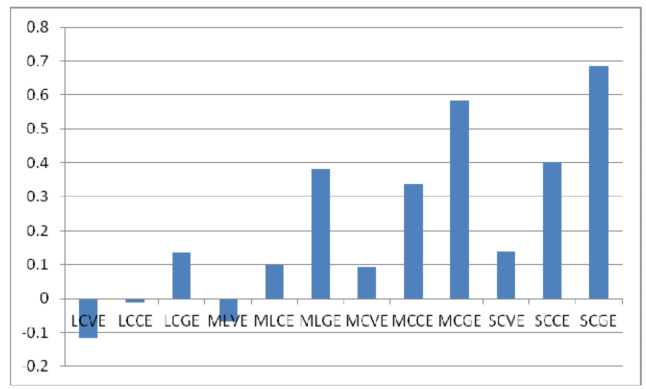
Exposure to Large-Value



Exposure to Large-Growth



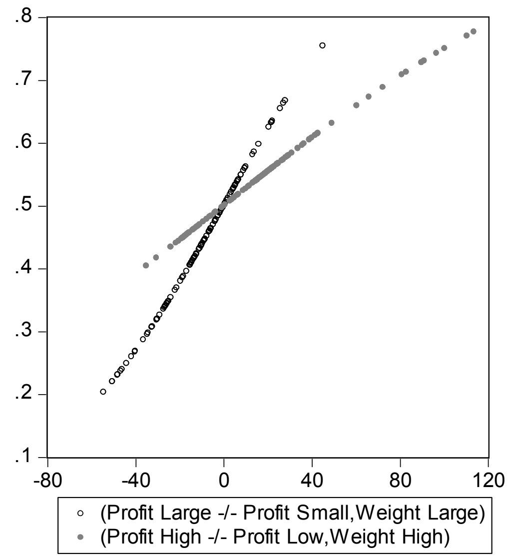
Exposure to Small-Value



Exposure to Small-Growth

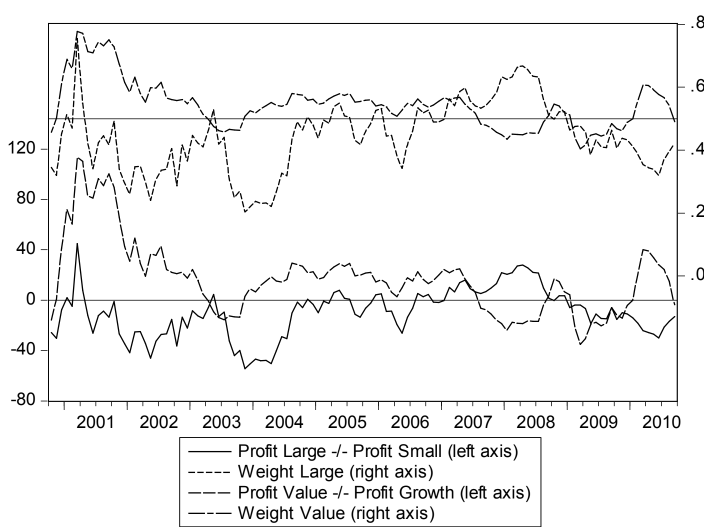
Notes: Figure 1 displays the average loadings to the four benchmark portfolios (y-axis) within the 12 fund classes (x-axis), estimated from Equation (4).

Figure 2. Scatter Plot of Profit Difference versus Weight: Oppenheimer



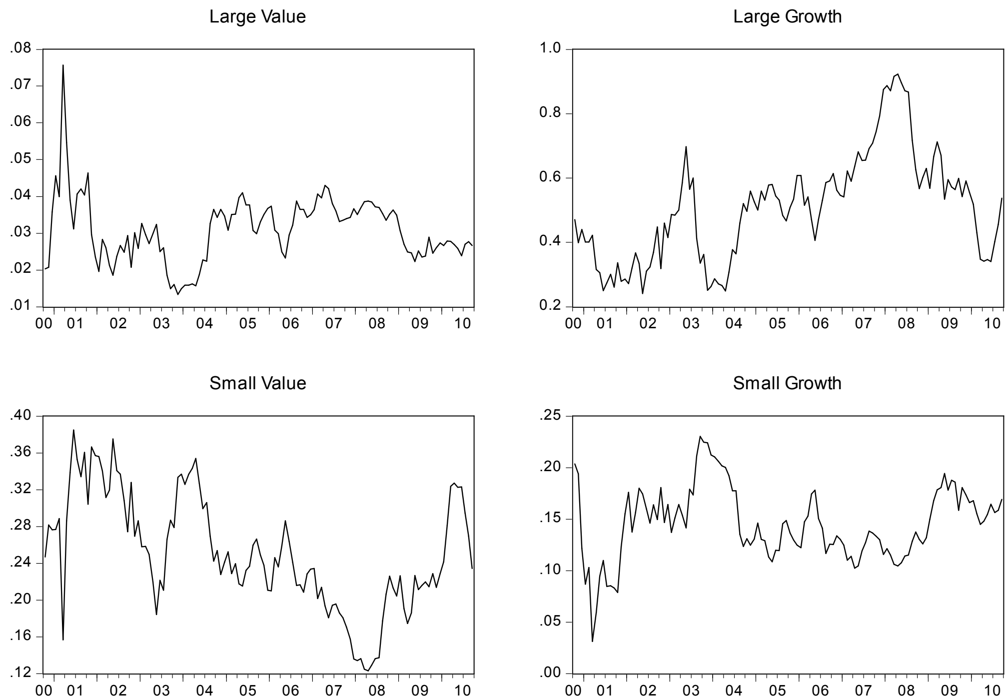
Notes: Figure 2 depicts a scatter plot of the profit difference (x-axis) versus the weight (y-axis) for the Oppenheimer fund, for both the size-switching and the book-to-market switching.

Figure 3. Time Series of Profit Differences and Weights: Oppenheimer



Notes: Figure 3 gives the time-series of the profit differences and the weights for the Oppenheimer Funds.

Figure 4. Time Series of Conditional Exposures $w_{it}\beta_i^k$: Oppenheimer



Notes: Figure 4 displays the conditional exposures, given by $w_{it}\beta_i^k$, to the four benchmark portfolios.