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On the Style-Based Feedback Trading of Mutual Fund Managers

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Abstract

This paper examines the style-based feedback trading behavior of U.S. mutual fund managers. We provide an empirical version of Barberis and Shleifer's style-switching model. 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, where capital is channeled between value and growth, and between large- 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.

I. Introduction

In this paper, we examine the style-based feedback trading of U.S. mutual fund managers. Understanding the investment behavior of fund managers is important, as they represent a large proportion of investors in the U.S. equity market. At the fund level, the behavior of the fund manager may have a large impact on fund performance and the fees charged. By examining 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 is closely related to the theoretical framework of Barberis and Shleifer (2003). Second, we empirically implement our model by examining the behavior of fund managers with respect to style investing, style-based

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feedback trading, "twin styles," and performance. We find strong evidence of style-based feedback trading among U.S. mutual fund managers in a way that is consistent with the framework of Barberis and Shleifer.

One of the great success stories in finance is the development of the mutual fund industry, which has undergone tremendous growth in terms of capital invested and the number and diversity of funds.[1] With this enormous growth and diversity, many funds classify themselves into investment styles to distinguish themselves and provide information about their asset allocation. Returns of funds following a particular style will, to a large extent, be driven by the performance of that style. However, because there is competition between funds for fund flow (Sirri and Tufano (1998)), funds may wish to increase their exposure to particular styles that are expected to outperform. Evidence for such behavior has been documented in several studies, including Cooper, Gulen, and Rau (2005), who find that funds have a tendency to change their name to take advantage of "hot" investment styles, and by Wermers (2012), who shows that there is "style drift" in mutual funds, which is partly deliberate and is chasing style returns.[2]

Several studies have explored whether changes in investment style can improve fund performance, with mixed results. Levis and Liodakis (1999) show that style rotation improves performance. Teo and Woo (2004) and Chen and Wermers (2005) show that changing to more profitable styles improves fund performance. In contrast, Chan, Chen, and Lakonishok (2002) find that style drift results in poor performance. In addition, Brown and Harlow (2005) find style consistency results in less turnover and greater performance persistence. Brown, Harlow, and Zhang (2011) find that less style-volatile funds produce greater risk-adjusted returns.

Chasing style returns is consistent with the theoretical "style investing" model of Barberis and Shleifer (2003), where investors classify assets into styles and make allocations at the style level by comparing the past performance of different investment styles. We refer to this as style-based feedback trading. Although some of the empirical predictions of Barberis and Shleifer have been tested by several studies (e.g., Teo and Woo (2004), Pomorski (2004)), 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. 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 asset allocation at the style level and act as style-based feedback traders.[3]

We implement the model of Barberis and Shleifer (2003) empirically by using a discrete choice model following Manski and McFadden (1981) and

[1] According to the 2014 Investment Company Fact Book, at the end of 2013, the U.S. mutual fund industry maintained $15 trillion in assets under management (AUM).

[2] In addition, Brown, Harlow, and Starks (1996) show that fund managers engage in "tournament behavior," where funds increase risk in later periods, if they underperform their peers.

[3] This paper relates to several studies on investor behavior. Grinblatt, Titman, and Wermers (1995) find that 77% of funds have a tendency to buy past winners. Bange (2000) shows that portfolio adjustments of individual investors reflect past market movements. In addition, Keim and Madhavan (1995) find 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 of individual investors in index funds and find that some investors act as positive feedback traders, while others act as negative feedback traders.

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employing concepts of the adaptive rational equilibrium framework proposed by Brock and Hommes (1997), who propose a model where economic agents choose between investment strategies (i.e., functions of past information), using a discrete choice model, and select the strategy that produced the highest profits in the recent past. While this model can be generally implemented to examine style investing and style-based feedback trading, we focus on U.S. domestic equity funds. Specifically, we estimate a model in which fund returns have time-varying exposures to several benchmark portfolios, where the time variation is conditional on lagged style returns.

We use the survivorship-free Center for Research in Security Prices (CRSP) mutual fund database over the period Dec. 1961–Sept. 2010 to examine style-based feedback trading behavior in U.S. domestic equity funds. We classify funds into different styles using Lipper classification codes based on size and value–growth orientation. We assess switching behaviors of fund managers using four benchmark portfolios/styles from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french) (large value (LV), small value (SV), large growth (LG), and small growth (SG)), which allow 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) and Grinblatt, Titman, and Wermers (1995), who find that momentum investing occurs in 77% of index funds. Notably, we find that some fund managers act as positive feedback or momentum traders (as suggested by Barberis and Shleifer (2003)), while others act as negative feedback or contrarian traders.[4] These findings are consistent with the trading behavior of individual investors in index (Goetzmann and Massa (2002)) and style (Blackburn, Goetzmann, and Ukhov (2014)) funds but have not yet been documented for fund managers. Our findings also support Wermers (2012), who shows that managers tend to be active "style chasers." We extend his work by giving more structure in the form of "twin style" feedback trading, as suggested by Barberis and Shleifer, and by relating this to fund characteristics, performance, and fund flows.

Second, we examine how the style-based feedback trading strategy is financed. As we study long-only domestic equity funds, which have equity exposures of close to 100%, 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 support the existence of twin styles, where investors switch between styles at opposite ends of the spectrum (e.g., an increase in the allocation to value stocks is financed by a decrease in the allocation to growth stocks). For the funds that engage in style-based feedback trading, the majority

In an extension, Blackburn, Goetzmann, and Ukhov (2014) find that investors adopt different trading strategies depending on the characteristics of the assets being traded.

[4]Following Goetzmann and Massa (2002) 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.

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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 fund's style.

Third, we find that there is more evidence of growth fund managers following a positive feedback rule and value fund managers following a negative feedback rule. This has been observed in the trading behavior of individual investors (Blackburn et al. (2014)), but has not yet been documented in the behavior of institutional investors.

Fourth, 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 relation with the fund's turnover. Subsequently, we evaluate whether style-based feedback trading leads to increased performance or attracts fund flow.[5] 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. 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. Brown et al. (2011) find that fund performance decreases in style volatility. We extend their work by showing that style volatility may be split into positive and negative feedback trading with different effects on risk-adjusted outperformance.

II. Empirical Model

Barberis and Shleifer (2003) propose a style investing model in a market where some investors switch between investment styles based on their past relative performance (referred to as switchers) and others are fundamental traders who act as arbitrageurs. In this section, we develop an empirical model following Barberis and Shleifer in which fund managers switch between investment styles and thus act as style-based feedback traders.[6]

According to Barberis and Shleifer (2003), switchers allocate more capital to a particular style if it performed relatively well in the recent past and finance this by allocating less to styles with relatively poor past performance. These switchers are assumed to have a specific lookback period, over which they compare the performances of different investment styles, and have a specific degree of style persistence (i.e., sensitivity to differences in past performances of investment styles). In addition, switchers are less willing to switch between asset classes.

[5]Evidence on the profitability of style timing is mixed. Swinkels and Tjong-A-Tjoe (2007) find profitable switching with respect to market timing and value–growth but not size dimensions. Budiono and Martens (2009) find that managers who time styles generate significant outperformance. Grinblatt et al. (1995) find outperformance of momentum traders compared with other funds. By contrast, Brown et al. (2011) show that funds that switch aggressively underperform relative to funds with less style volatility.

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

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This implies that switching between styles is mostly self-financed within a specific asset class. Finally, Barberis and Shleifer suggest that switchers prefer to switch between twin styles, where an increased allocation to growth (small-cap) stocks is financed by a decreased allocation to value (large-cap) stocks.

The functional form of the switching mechanism in the theoretical model of Barberis and Shleifer (2003) cannot be directly implemented to our analysis of mutual funds, for several reasons. First, Barberis and Shleifer model the demand for assets. However, mutual funds might also demand stocks because of capital inflows. Therefore, we focus on portfolio weights, because changes in weights imply changes in investment strategy.[7] Second, their switching model considers only two styles, whereas we consider four. A priori, it is not clear how to generalize their switching mechanism to more than two styles.

We empirically model style switching using the multinomial choice model introduced by Brock and Hommes (1997). They consider a market for a single asset in which investors can switch between different trading strategies, based on recent relative performance. The assumptions regarding investor behavior in Brock and Hommes (1997) are very similar to those in Barberis and Shleifer (2003). Specifically, investment decisions are made based on expected returns, which are based on past returns. In both models, the lookback period, the period over which past performance is considered, is an important input in the switching decision, and the aggressiveness of switching is captured by a parameter. Additionally, the portfolio weights of the multinomial choice model are between 0 and 1, prohibiting short selling, and add up to 1, consistent with the self-financing feature of Barberis and Shleifer.

The main difference between Barberis and Shleifer (2003) and Brock and Hommes (1997) is that in Brock and Hommes (1997) switching occurs between different rules to forecast the returns of a single asset, whereas switching in Barberis and Shleifer occurs between different assets using one forecasting rule. The functional form of the switching mechanism in Brock and Hommes (1997) can thus be seen as a generalization of Barberis and Shleifer.

The multinomial choice function of Brock and Hommes (1997) has several desirable features. First, it introduces continuous time-varying exposures to different investment styles that permit transforming a static model into a dynamic one. Second, this function allows the inclusion of any variable that triggers fund managers to change their investment style. In this paper, we use the past performance of different investment styles.[8] Third, this function leads to a parsimonious model, which, in the simplest specification, consumes only one additional degree of freedom compared with a static specification. Finally, it is more general than the functional form of Barberis and Shleifer (2003), as it allows for contrarian as well as momentum behavior.

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

[7]In Barberis and Shleifer (2003), the relative demand for assets in style X is equivalent to the portfolio weight on style X because there is 0 net capital inflow.

[8]Other potential decision variables include other funds' exposures (herding) or their own returns relative to the benchmark (tournament behavior).

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 performance measure of investment style k in period $t-1$, and J is the manager's lookback period ($j = 1, \ldots, J$).[9]

In the multinomial switching rule of Brock and Hommes (1997), (1998), the weight that manager i puts on investment style k at time t is defined as

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

where γ_i is the intensity of choice parameter. This parameter captures a manager's sensitivity to the past profits of different investment styles and determines the aggressiveness by which he or she switches between different investment styles. If $\gamma_i = 0$, the manager does not respond to differences in relative profitability and does not switch; in this case, $w_{it|t-1}^k = w^k = 1/K$. At the other extreme, if $|\gamma_i| \to \infty$, the manager fully allocates her or his investments to the style that had the highest recent performance. A positive value for γ_i indicates that the manager puts more weight on styles that have performed relatively well in the recent past and thus behaves as a positive feedback (momentum) trader. A negative value for γ_i indicates that the manager acts as a negative feedback (contrarian) trader.

Based on the stated investment style of a 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; that is,

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

where r_{it} is the return of funds i at time t, α_i captures the out- or underperformance of the fund, and β_i^k captures the unconditional exposure to investment style k. We include unconditional exposures, as fund managers typically classify themselves as following a particular investment style. For example, a fund that classifies itself as a growth fund would have an unconditionally greater exposure to the growth investment style. Including β_i^k in equation (3) allows a fund to have an unconditional exposure to its stated investment style, and $w_{it|t-1}^k$ allows for deviations from these unconditional exposures and introduces time variation.

III. Data

We estimate the model presented in Section II using the survivorship-bias free CRSP Mutual Fund Database. We collect monthly mutual fund data from

[9] Barberis and Shleifer (2003) employ a process to capture the memory of investors. We apply a discrete measure following Blackburn et al. (2014).

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Dec. 1961 to Sept. 2010 for U.S. domestic equity retail funds with more than $10 million AUM, excluding index tracking funds. We remove funds with less than 36 observations to obtain meaningful estimates.

Brown and Goetzmann (1997), (2001) note that a key issue in mutual fund research is that funds misclassify themselves. We address this issue in the following way. First, we classify funds on the basis of Lipper codes. These codes are based on the portfolio holdings as reported by the funds. Lipper classifies funds into 12 styles based on the size and value/growth orientation of the holdings of the fund: 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). However, as pointed out by Brown and Goetzmann (1997), funds may engage in window dressing. Hence, we check the consistency of a fund's returns 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 (small minus big) factor and the HML (high minus low) factor.[10] 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., a positive loading on SMB if the fund classifies itself as small cap, a negative loading if it classifies itself as large cap, etc.). Our sample is composed of 2,044 unique U.S. domestic equity funds.[11]

In Table 1, we report summary statistics. All fund types are well represented; MCVE has the fewest funds in the sample (96), while MLCE has the greatest number of funds (326). The median average return shows considerable variation

TABLE 1

Mutual Fund Descriptive Statistics

Table 1 presents descriptive statistics for the mutual funds in the sample. LC, ML, MC, and SC represent large-cap, multi-cap, mid-cap, and small-cap, respectively. VE, CE, and GE represent 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. SHARPE is the annual Sharpe ratio calculated as RETURN/STDEV. RETURN, STDEV, MIN, and MAX are presented as monthly percentages.

		MEDIANS					
STYLE	FUNDS	RETURN	STDEV	SHARPE	MIN	MAX	No. of Obs.
LCVE	128	0.686%	4.860%	0.481	−18.108%	9.716%	125
LCCE	208	0.667%	4.931%	0.508	−18.049%	9.471%	104.5
LCGE	128	0.530%	5.535%	0.326	−19.438%	11.213%	114
MLVE	239	0.663%	4.973%	0.559	−19.787%	10.498%	122
MLCE	326	0.731%	5.034%	0.589	−18.970%	9.999%	89.5
MLGE	184	0.756%	6.253%	0.434	−22.262%	13.280%	124
MCVE	96	0.916%	5.567%	0.499	−23.026%	13.138%	112.5
MCCE	120	0.976%	6.041%	0.476	−24.471%	13.473%	98
MCGE	145	0.848%	7.225%	0.416	−25.184%	17.658%	93
SCVE	163	0.943%	6.006%	0.551	−23.089%	13.940%	123
SCCE	168	1.024%	6.462%	0.567	−23.409%	14.662%	92
SCGE	139	0.944%	7.536%	0.425	−26.892%	20.709%	110

[10]We use the data provided on Kenneth French's Web site: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

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

over the various investment styles; LCGE has the lowest monthly average return, 0.530% (about 6.5% per annum), and SCCE has the highest average return, 1.024% (about 13% per annum). These averages demonstrate the presence of a size effect, where small-cap funds generally outperform large-cap funds. The growth effect is less pronounced in this table. Investment styles with higher risk tend to yield higher average returns.

We also obtain data on the following fund characteristics from the CRSP Mutual Fund Database: total expense ratio (TER), age (AGE), total net assets (TNA), and turnover (TURNOVER). In Table 2, we report summary statistics on these characteristics. The average TER is 1.41%. In general, growth funds have higher TERs than value funds (consistent with Carhart (1997)) and small-cap funds charge higher TERs than large-cap funds (consistent with Brown et al. (2011)). The average age of the funds is 14.24 years, with core equity funds tending to be younger than value or growth funds and small-cap funds tending to be younger than large-cap funds. The average size of our funds is $418.5 million, and large-cap funds tend to be larger than small-cap funds. The average turnover ratio is 83.30%, which is broadly consistent with the ratios presented by Carhart and Brown et al. (2011). Consistent with these studies, we find that growth (small-cap) funds have higher turnover ratios than value (large-cap) funds. These summary statistics suggest that our sample has similar properties to those of Carhart and Brown et al. (2011).

To examine the style-switching behavior of fund managers, we relate the performance of each fund to the performance of benchmark portfolios. These benchmark portfolios are obtained from Kenneth French's data library. Instead of using the typical style factors, SMB and HML, we employ the individual portfolios. In particular, we use the LV, LG, SV, and SG portfolios.

Panel A of Table 3 presents descriptive statistics for the benchmark portfolios. The mean returns show variation across the styles, consistent with prior literature (Fama and French (1993)). The highest average return is observed for SV (1.424% per month), while LG has the lowest average return (0.816% per month). We observe that the value effect is more prominent in small-cap portfolios than in large-cap portfolios. In Panel B, we report the correlations between the benchmark portfolios. Because these are long-only portfolios, the correlations are relatively high.

IV. Style and Style-Based Feedback Trading

In this section, we present the estimation results of our model. First, we present results for constant style exposures. Next, we report the results for two models where managers can either switch between all four styles (e.g., financing investments in growth stocks by selling small-cap stocks) or switch between twin styles (between value–growth and large–small separately).

A. Unconditional Fund Exposures

To examine whether funds follow their stated investment style, we run a regression of the excess returns of each individual fund on the different investment

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TABLE 2

Fund Characteristics

Table 2 presents summary statistics on fund characteristics. We present the values for the mean, the standard deviation, and the 5th (P5), 50th (P50), and 95th (P95) percentiles. We report statistics for the total expense ratio (TER), fund age (AGE), total net assets (TNA), and turnover (TURNOVER) for all funds and per fund category.

	ALL	LCVE	LCCE	LCGE	MLVE	MLCE	MLGE	MCVE	MCCE	MCGE	SCVE	SCCE	SCGE
Panel A. TER													
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%
P5	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%
P50	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%
P95	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%
Panel B. 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
P5	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
P50	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
P95	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
Panel C. TNA (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.	1,754.5	1,348.2	4,394.0	2,584.5	766.5	1,285.3	1,302.1	656.4	1,084.6	286.9	941.6	358.3	372.4
P5	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
P50	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
P95	1,598.5	2,911.7	2,056.7	6,338.3	1,573.7	2,326.7	2,243.4	1,814.3	2,937.0	755.3	1,500.3	640.1	663.1
Panel D. 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%
P5	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%
P50	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%
P95	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%

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TABLE 3
Descriptive Statistics for the Benchmark Portfolios

Table 3 presents descriptive statistics for the four benchmark portfolios. SV, SG, LV, and LG represent small value, small growth, big value, and big growth, respectively, retrieved from Kenneth French's data library.

	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	21.09%	21.26%	30.27%	28.88%
Minimum	−22.64%	−23.23%	−27.72%	−32.34%
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

styles; that is,

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

where r_t^{SV}, r_t^{SG}, r_t^{LV}, and r_t^{LG} are the returns on the SV, SG, LV, and LG portfolios, respectively.

Figure 1 presents box-and-whisker plots of the unconditional loadings on the different investment styles. This plot shows two patterns. First, loadings on LV and SV decrease from value to core to growth, whereas loadings on LG and SG increase. Second, when moving from large- to multi- to mid- to small-cap, the loadings on LV and LG decrease, whereas the loadings on SV and SG increase.[12] Overall, our findings suggest that funds behave unconditionally according to their stated styles.

B. Style-Based Feedback Trading of Fund Managers

To examine whether managers switch between investment styles, we estimate a model in which managers can switch between all styles (single-switching), and then we estimate a model in which switching occurs according to twin styles (double-switching).

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

$$\begin{aligned} r_{it} = {} & \alpha_i + w_{it|t-1}^{\mathrm{SV}} \beta_i^{\mathrm{SV}} r_t^{\mathrm{SV}} + w_{it|t-1}^{\mathrm{SG}} \beta_i^{\mathrm{SG}} r_t^{\mathrm{SG}} \\ & + w_{it|t-1}^{\mathrm{LV}} \beta_i^{\mathrm{LV}} r_t^{\mathrm{LV}} + w_{it|t-1}^{\mathrm{LG}} \beta_i^{\mathrm{LG}} r_t^{\mathrm{LG}} + \varepsilon_{it}, \end{aligned} \tag{5}$$

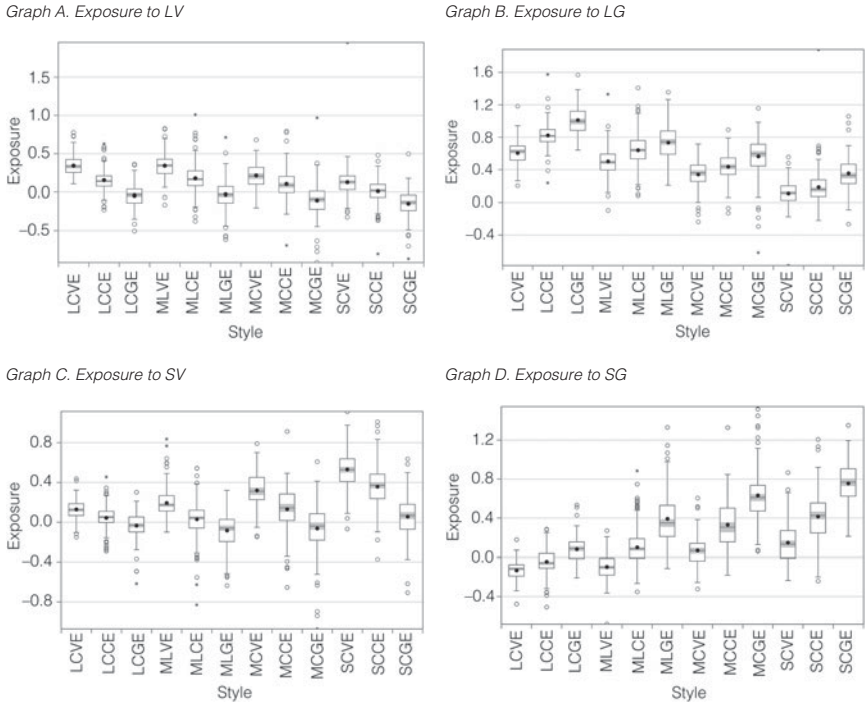
[12] We have also conducted t-tests of differences in unconditional exposures between styles (p-values of this test are available from the authors). The differences between styles are statistically significant, apart from certain styles that have overlapping strategies, such as MLGEs and LCGEs exposed to the LV portfolio.

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FIGURE 1

Unconditional Loadings on the Different Investment Styles

Figure 1 displays the cross-sectional distribution of loadings to the four benchmark portfolios (*y*-axis) within the 12 fund classes (*x*-axis), estimated from equation (4).



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

$$
\begin{aligned}
(6) \qquad \pi^{\mathrm{SV}}_{kt-1} &= \sum_{j=1}^{J} \mathrm{SV}_{t-j}, \qquad \pi^{\mathrm{SG}}_{kt-1} = \sum_{j=1}^{J} \mathrm{SG}_{t-j}, \pi^{\mathrm{LV}}_{kt-1} \\
&= \sum_{j=1}^{J} \mathrm{LV}_{t-j}, \qquad \pi^{\mathrm{LG}}_{kt-1} = \sum_{j=1}^{J} \mathrm{LG}_{t-j}.
\end{aligned}
$$

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; that is,

$$
\begin{aligned}
(7) \qquad r_{it} &= \alpha_i + w^{\mathrm{SIZE}}_{it|t-1} w^{\mathrm{BM}}_{it|t-1} \beta_{1i} \mathrm{SV}_t + w^{\mathrm{SIZE}}_{it|t-1} \left(1 - w^{\mathrm{BM}}_{it|t-1}\right) \beta_{2i} \mathrm{SG}_t \\
&\quad + \left(1 - w^{\mathrm{SIZE}}_{it|t-1}\right) w^{\mathrm{BM}}_{it|t-1} \beta_{3i} \mathrm{LV}_t \\
&\quad + \left(1 - w^{\mathrm{SIZE}}_{it|t-1}\right) \left(1 - w^{\mathrm{BM}}_{it|t-1}\right) \beta_{4i} \mathrm{LG}_t + \varepsilon_{it},
\end{aligned}
$$

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

$$
\begin{aligned}
\pi^{\text{LARGE}}_{kt-1} &= \sum_{j_l=1}^{J_l} (\text{LV}_{t-j_l} + \text{LG}_{t-j_l}), \\
\pi^{\text{SMALL}}_{kt-1} &= \sum_{j_l=1}^{J_l} (\text{SV}_{t-j_l} + \text{SG}_{t-j_l}), \\
\pi^{\text{VALUE}}_{kt-1} &= \sum_{j_l=1}^{J_l} (\text{LV}_{t-j_l} + \text{SV}_{t-j_l}), \\
\pi^{\text{GROWTH}}_{kt-1} &= \sum_{j_l=1}^{J_l} (\text{LG}_{t-j_l} + \text{SG}_{t-j_l}),
\end{aligned} \tag{8}
$$

where $\pi^{\text{LARGE}}_{kt-1}$, $\pi^{\text{SMALL}}_{kt-1}$, $\pi^{\text{VALUE}}_{kt-1}$, and $\pi^{\text{GROWTH}}_{kt-1}$ are the profitability of the large-cap, small-cap, value, and growth investment styles, respectively. The weights are computed according to equation (2). Because equation (7) has two different weights, we estimate two intensity-of-choice parameters (γ^{SIZE} and γ^{BM}) and estimate equation (7) in three ways. First, we set γ^{SIZE} equal to 0 (allowing for switching in the value–growth dimension only). Second, we set γ^{BM} equal to 0 (allowing for switching in the size dimension only). Third, we allow for switching in both directions simultaneously.

Equations (2), (5), and (6) for the single-switching case, and equations (2), (7), and (8) for the double-switching case, can be combined into a single nonlinear equation. We employ quasi-maximum likelihood to estimate α_i, the four β^k_i, and γ_i. 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 likelihood.[13]

1. The Case of the Oppenheimer Main Street Opportunity Fund

To provide some elucidation about the underlying dynamics of our model, we present detailed results for the Oppenheimer Main Street Opportunity Fund, CRSP fund number 23076, chosen at random from the funds that have significant switching. The fund is classified as MLCE with data from Sept. 2000 to Sept. 2010. At the end of the sample, the fund had $11.6 million AUM.

Table 4 presents the estimation results for the Oppenheimer fund. The static model shows that the fund has significant exposures to LG and SV. Hence, both the multi-cap and the core-equity characteristics of the fund are well represented. To interpret the magnitude of the β's, we must divide the coefficients by 4, because $\gamma = 0$ in the static model 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.

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

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TABLE 4

Estimation Results for the Oppenheimer Main Street Opportunity Fund

Table 4 presents the estimation results of the static model (column 1), the single-switching model (column 2), the twin style value-switching model (column 3), the twin style size-switching model (column 4), and the double twin style model (column 5) for the Oppenheimer Main Street Opportunity Fund. The single-switching model allows for fund managers to switch between all styles, whereas the twin style model allows only for switching between styles at opposite sides of the spectrum (i.e., between value vs. growth and large vs. small). We select the optimal lag length by estimating the model for $j = 1$ to 12; we choose the optimal value, j^*, by selecting the specification with the highest log-likelihood (LOGL). 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. * and ** indicate significance at the 5% and 1% levels, respectively.

			Twin Style		
	Static Model	Single γ	Value	Size	Double
	1	2	3	4	5
β^{LV}	0.309 (0.913)	0.000 (0.002)	−0.038 (−0.142)	0.554 (1.601)	0.129 (0.441)
β^{LG}	1.574** (3.844)	2.253** (3.631)	2.274** (4.135)	1.756** (4.221)	2.510** (4.961)
β^{SV}	1.117** (3.238)	0.975** (3.429)	1.112** (4.310)	0.838* (2.138)	0.824** (2.896)
β^{SG}	0.598 (1.886)	0.605 (1.395)	0.568 (1.560)	0.564 (1.720)	0.573 (1.707)
γ		0.021** (2.779)			
γ^{BM}			0.013** (2.600)		0.011* (2.557)
γ^{SIZE}				0.024 (1.201)	0.025 (0.020)
α	−0.130 (−0.197)	−0.129 (−0.450)	−0.194 (−0.724)	−0.098 (−0.389)	−0.143 (−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*

Column 2 of Table 4 presents the results for the single-switching model (equations (5) and (6)). 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.[14] The fact that γ is positive suggests that this fund manager 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, $j^* = 12$.

Columns 3–5 of Table 4 present the results for the double-switching models (equations (7) and (8)). For the Value twin style model, we find that γ is positive and significant, suggesting that the fund manager acts as a positive feedback trader. This is confirmed by the LR test versus the static model. For the Size twin style model, we find an insignificant γ and LR statistic, suggesting that this fund does not switch in the size dimension. Column 5 shows the results for the Double twin style model. We observe that γ^{BM} is significant and γ^{SIZE} is not. The LR

[14]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.

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statistic for this model is significantly higher than the static one. The LR statistics for the Double twin style model versus the Value and Size twin style models show that the Double twin style model improves significantly on the Size twin style model, but not on the Value twin-style model. Thus, this fund displays only positive feedback trading in the value–growth dimension.

In Figure 2, we plot the relation between the performance difference for value–growth and size ($\pi^{\text{VALUE}} - \pi^{\text{GROWTH}}$ and $\pi^{\text{LARGE}} - \pi^{\text{SMALL}}$) versus the weight put on value and large-cap stocks (w^{VALUE} and w^{LARGE}) for the double-switching model. For both relations, we observe a positive relation between past performance and current exposure due to the positive values for γ^{BM} and γ^{SIZE}. The curve for the size switching is steeper than that for the value–growth switching, because $\gamma^{\text{SIZE}} > \gamma^{\text{BM}}$. 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 under- or outperforms the growth benchmark by 40% over the previous year. In the size dimension, similar large- and small-cap model under- or outperformance leads to a change in weight on large-cap from about 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, implying that value stocks outperformed growth stocks and small-caps outperformed large-caps over the sample period.

FIGURE 2

Scatter Plot of Profit Difference versus Weight: Oppenheimer

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 (in black) and the book-to-market switching (in gray).

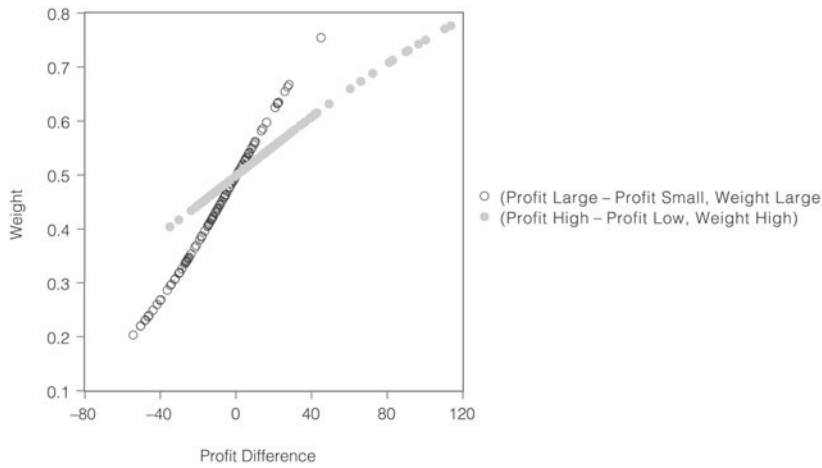


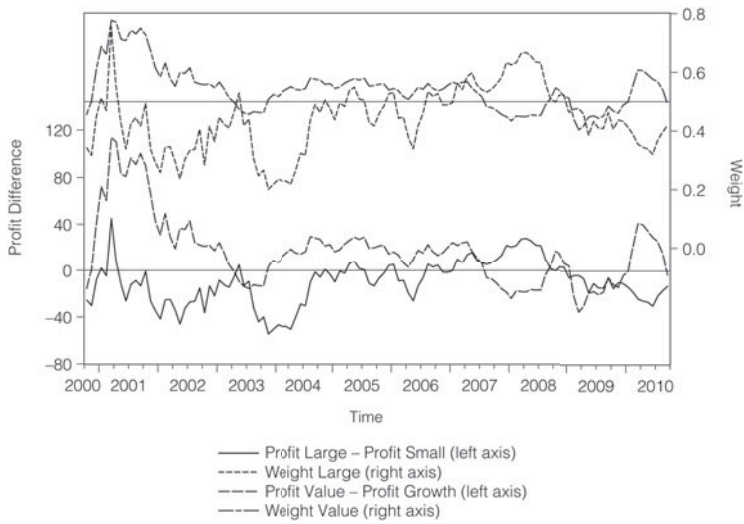
Figure 3 shows the profit differences and weights in a time-series plot in which the upper part of the graph shows the weights, w^{VALUE} and w^{LARGE}, and the lower part of the graph shows the performance differences ($\pi^{\text{VALUE}} - \pi^{\text{GROWTH}}$ and $\pi^{\text{LARGE}} - \pi^{\text{SMALL}}$). There is substantial time variation in the value and size weights, roughly ranging from 0.2 to 0.8. During 2001 and 2002, value stocks outperformed growth stocks, which caused the weight on value firms to be high. After 2002, the value premium remains slightly positive, causing the average

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FIGURE 3

Time Series of Profit Differences and Weights: Oppenheimer

Figure 3 gives the time series of the profit differences (left axis) and the weights (right axis) for the Oppenheimer funds.



value weight to be slightly above 0.5. The size premium is close to 0 throughout the entire period, except for the peak in 2001, which caused the fund manager to increase the weight on large-caps. From late 2003 to the middle of 2004, large-caps underperformed small-caps, which decreased the weight on large-caps to its low of about 0.2.

Figure 4 presents a time-series plot of the conditional exposures to the four benchmark portfolios given by multiplying the time-varying weights w_{it} with the unconditional exposures β_i^k. Graph A shows the conditional beta on LV. Consistent with Table 3, the exposure to LV is low, although there is some variation in the conditional beta. Graph B shows the conditional beta for LG. The unconditional loading on this portfolio was greatest. Figure 4 shows it has the largest absolute variation ranging from 0.25 in late 2001–early 2002 and again in early 2004 to 0.9 near the beginning of 2008. This suggests that there are substantial shifts in the exposure of this fund to LG. Graph C shows the conditional beta of SV. There is again considerable variation in the conditional exposure, peaking from the middle of 2001 to the middle of 2002 and bottoming out at the beginning of 2008. Finally, Graph D shows the conditional exposure to SG. We again observe considerable time variation in the conditional exposure to SG, from a low in the beginning of 2001 to a high in 2003–2004.

2. Style-Based Feedback Trading in U.S. Domestic Equity Funds

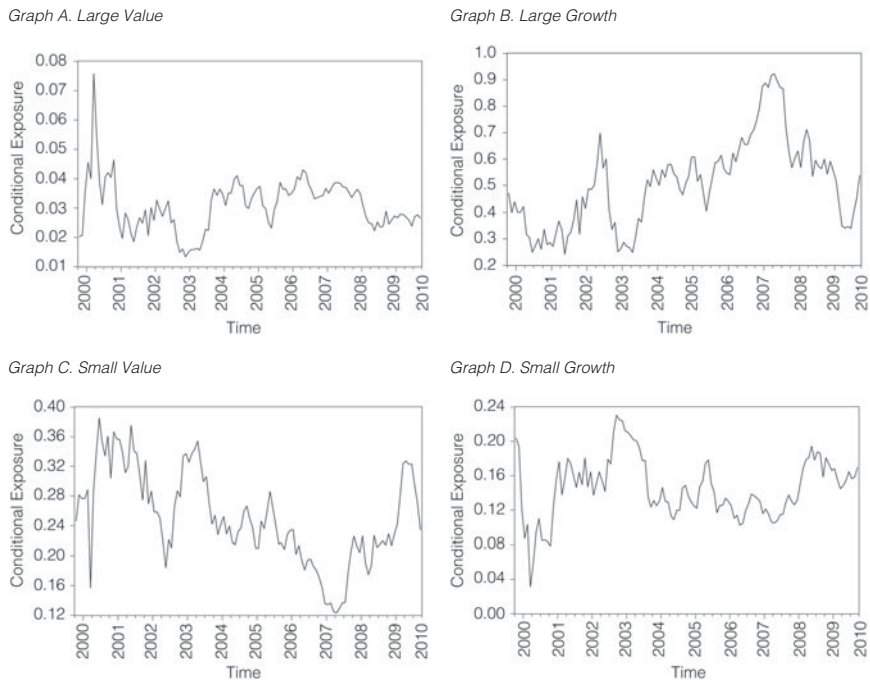
We estimate the single and twin style-switching models for all funds in our sample and present summary statistics in Table 5. In Panel A, we report the percentage of funds where the likelihood of the single γ model increases significantly at the 5% level compared with the static model, along with the percentage

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FIGURE 4

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

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



of funds with significant positive and negative γ.[15] Overall, we find considerable improvements in model fit when we allow for switching behavior, with significant switching for approximately 53% (23% positive and 30% negative) of the funds in our sample. The greatest significance in switching is reported for MCVE (68%), while the least significance is found for LCGE (44%). This suggests that style-based feedback trading is prevalent among many fund managers and across styles.

We split the percentage of significant switching into positive and negative feedback trading. For all size groups, we observe a clear trend with more positive feedback trading for growth funds and more negative feedback trading for value funds. This difference is statistically significant at the 1% level for all groups, except large-cap funds.[16] This suggests that the type of feedback trading followed

[15]The results in Table 5 are based on comparison of the LR statistic with the critical values of a χ^2-distribution. In the Appendix, we provide a robustness test, where we reproduce Table 5 based on a bootstrap, although the overall percentage of funds engaging in switching behavior is somewhat lower than presented in Table 5 (38% (68%) of funds engaging in single (double) switching when using the bootstrap versus 53% (77%) according to the χ^2-distribution). The observed patterns in Table 5 largely remain in the bootstrap results.

[16]For each style, we test whether the difference between positive and negative feedback trading is significant using a χ^2 statistic. Likewise, we test whether significant positive or negative feedback trading between value and growth is significantly different using a *t*-test.

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TABLE 5

Percentage of Switching Funds

Table 5 presents the percentage of funds for which we find significant switching. Specifically, we present the percentage of funds for which the likelihood ratio test indicates that switching adds significantly (at the 5% level) to the explanatory power of the model. Panel A represents results of the single-switching model versus the static model, and Panel B presents the results of the double-switching model versus the static model. We split results into positive and negative feedback trading and report the difference between positive and negative feedback trading in the row labeled POS − NEG. We test for the significance of this difference using a χ^2 statistic. We also compute the difference in style switching between the Value and Growth styles and report these differences in the columns labeled V − G. We test for the significance of this difference using a *t*-test. * and ** indicate significance at the 5% and 1% levels, respectively.

	ALL	LCVE	LCCE	LCGE	V − G	MCVE	MCCE	MCGE	V − G	MLVE	MLCE	MLGE	V − G	SCVE	SCCE	SCGE	V − G
Panel A. Single γ Model																	
Total	52.56	50.45	47.90	44.33	6.12	68.67	50.98	57.69	10.98	52.15	52.79	49.38	2.77	48.46	50.75	60.83	−12.37*
POS γ	22.61	12.84	13.77	20.62	−7.78	18.07	21.57	40.77	−22.70**	11.96	27.51	41.36	−29.40**	2.31	16.42	43.33	−41.02**
NEG γ	29.95	37.61	34.13	23.71	13.90*	50.60	29.41	16.92	33.68**	40.19	25.28	8.02	32.17**	46.15	34.33	17.50	28.65**
POS − NEG	−7.34**	−24.77**	−20.36**	−3.09		−32.53**	−7.84	23.85**		−28.23**	2.23	33.34**		−43.84**	−17.91**	25.83**	
Panel B. Twin Styles																	
Panel B1. Only Value Switching																	
Total	20.69	20.93	24.82	16.67	4.26	24.10	21.57	14.62	9.48	28.87	26.02	10.69	18.18**	11.29	25.98	15.13	−3.84
POS γ	5.96	0.00	4.26	5.95	−5.95**	4.82	6.86	8.46	−3.64	5.15	5.69	5.03	0.12	1.61	11.02	11.76	−10.15**
NEG γ	14.73	20.93	20.57	10.71	10.22*	19.28	14.71	6.15	13.13**	23.71	20.33	5.66	18.05**	9.68	14.96	3.36	6.32*
POS − NEG	−8.77**	−20.93**	−16.31**	−4.76		−14.46**	−7.85	2.31		25.83**	−14.64**	−0.63		−8.07**	−3.94	8.40*	
Panel B2. Only Size Switching																	
Total	17.62	25.58	12.06	8.33	17.25**	24.10	22.55	13.85	10.25*	10.82	14.23	19.50	−8.68**	29.84	16.54	24.37	5.47
POS γ	9.03	18.60	6.38	2.38	16.22**	10.84	11.76	10.77	0.07	6.19	7.72	13.84	−7.65**	0.81	7.09	15.97	−15.16**
NEG γ	8.59	6.98	5.67	5.95	1.03	13.25	10.78	3.08	10.17**	4.64	6.50	5.66	−1.02	29.03	9.45	8.40	20.63**
POS − NEG	0.44	11.62**	0.71	−3.57		−2.41	0.98	7.69*		1.55	1.22	8.18*		−28.22**	−2.36	7.57	
Panel B3. Double Switching																	
Total	38.87	29.06	32.62	38.08		36.14	34.31	54.62		40.21	36.99	43.40		42.74	29.14	44.55	
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. Total																	
Total	77.21	75.57	69.50	63.08	12.49*	84.34	78.43	83.09	1.52	79.90	77.24	73.59	6.30	83.8	71.6	84.0	−0.2

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is style dependent, and is notable in light of Blackburn et al. (2014), who find style-dependent trading strategies among individual investors. They show that individuals follow positive feedback strategies when buying growth funds but negative feedback strategies when buying value funds. Our results demonstrate that this behavior extends to fund managers.

Panel B of Table 5 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. This is consistent with Grinblatt et al. (1995), who find that 77% of funds display return chasing behavior. We observe several patterns in the differences between positive and negative feedback trading. For switching in the value dimension (Panel B1), we find that there is more positive feedback trading for growth funds across all size styles (significant for large- and small-cap funds) and more negative feedback trading in value funds (significant for all size groups). For switching in the size dimension (Panel B2), there is more positive feedback trading for growth funds (except for large-cap funds) and more negative feedback trading for value funds.

In Panel B3 of Table 5, we report results for the double twin style-switching model. The first row reports the percentage of funds for which the double twin style-switching model is best. In general, growth funds engage more often in double switching than value funds. However, there are no clear patterns in positive and negative feedback trading across the double twin styles.

Figure 5 presents the average sensitivity of the weights to profit differences, where we split funds into momentum and contrarian traders, in both the value and size dimensions. It is similar to Figure 2 but uses the cross-sectional average of γ and its 95% confidence interval instead. For all plots, there is a distinct S-shape induced by the switching function (see equation (2)). In Graphs A and B, we observe that the curves are upward sloping, illustrating that positive feedback traders allocate more capital to the style that performed better in the recent past. The curves in Graphs C and D are downward sloping, illustrating that negative feedback traders allocate more capital to the style that performed worse in the recent past. The plots in the right two graphs represent switching in the size dimension; these plots are slightly steeper than the plots for the value dimension. This implies that, on average, fund managers are slightly more sensitive to profit differences between large- and small-caps than they are to differences between value and growth stocks.[17] The upper bound of the 95% confidence interval displays a sharper S-shape than the average. At a profit difference of 50%, the upper bound reaches 0 or 1, whereas for the average, this was only at a profit difference of 100%. The lower bound is virtually a straight line; however, there is a certain slope, indicating that the funds with the lowest γ's still switch.

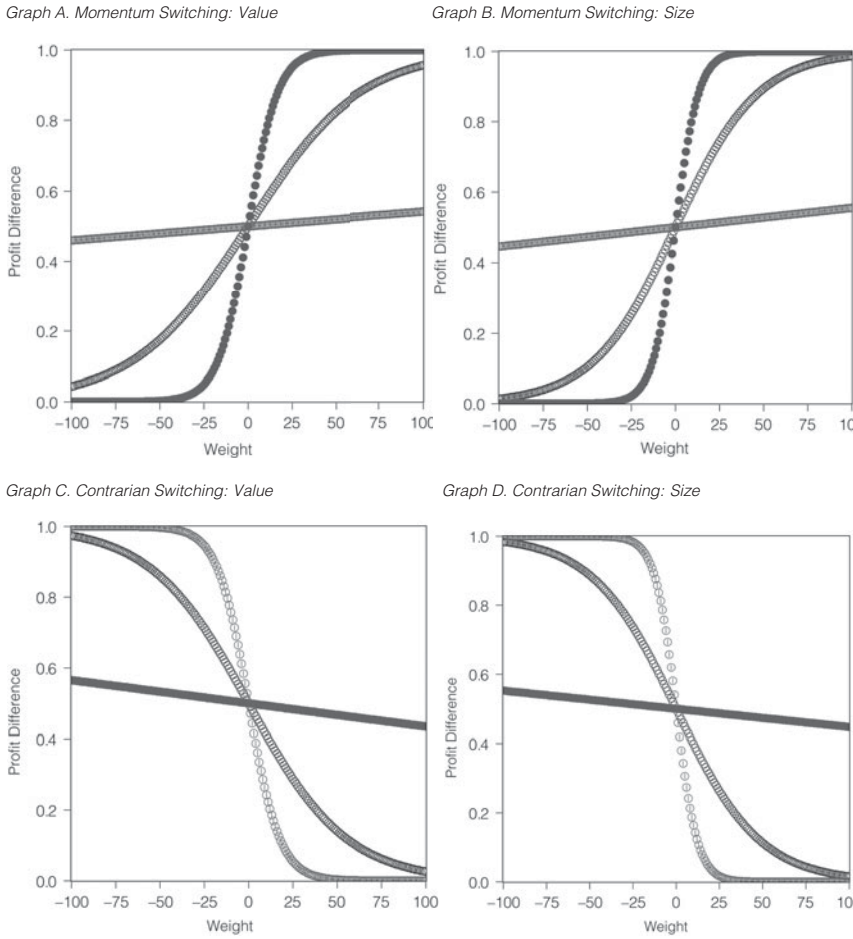
Figure 6 presents the average conditional betas for all funds, given by $w_{i,t}^{\text{SIZE}} w_{i,t}^{\text{BM}} \beta_i$, again split up in four categories: i) size momentum, value momentum ($\gamma^{\text{SIZE}} > 0$, $\gamma^{\text{BM}} > 0$, Graph A); ii) size contrarian, value momentum ($\gamma^{\text{SIZE}} < 0$, $\gamma^{\text{BM}} > 0$, Graph B); iii) size momentum, value contrarian ($\gamma^{\text{SIZE}} > 0$,

[17] This might be explained by the fact that the value premium is, on average, larger and more persistent than the size premium (see Fama and French (1993)).

FIGURE 5

Scatter Plot of Profit Difference versus Weight: All Funds

Figure 5 presents the average switching behavior of funds in four categories: i) momentum in the value dimension ($\gamma^{BM} > 0$, Graph A); ii) momentum in the size dimension ($\gamma^{SIZE} > 0$, Graph B); iii) contrarian in the value dimension ($\gamma^{BM} < 0$, Graph C); and iv) contrarian in the size dimension ($\gamma^{SIZE} < 0$, Graph D). The horizontal axis in each graph represents the profit differences, whereas the vertical axis represents the weight. Each graph contains a curve based on the average γ (middle curve) as well as the upper (steepest curve) and lower (flattest curve) bounds of the 95% confidence interval.



$\gamma^{BM} < 0$, Graph C); and iv) size contrarian, value contrarian ($\gamma^{SIZE} < 0$, $\gamma^{BM} < 0$, Graph D). Each graph is divided in four, representing the unconditional exposures to the large-value, small-value, large-growth, and small-growth portfolios, respectively. All figures include the 95% confidence intervals.

Figure 6 shows considerable time variation in the average conditional exposures to the four portfolios. For example, the exposure to the large-cap/growth portfolio for the momentum–momentum funds (Graph A) drops from 0.95 at the start of 1999 to 0.30 at the start of 2000. In a number of plots, we observe large changes in the unconditional exposures around the IT bubble (around 2000). The change in exposure depends on the particular type of behavior and portfolio.

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V. Style-Based Feedback Trading and Fund Characteristics

Section IV.B provides strong evidence of style-based feedback trading behavior in mutual fund managers. We next examine whether this behavior is related to fund characteristics.

Table 6 presents the univariate results, in which we sort funds on γ and create deciles. The first column shows the wide variety of switching tendencies of fund managers, which differs significantly between the top and bottom deciles. The lookback period increases monotonically over the deciles, indicating that funds that switch more aggressively have a shorter lookback period. Performance appears to improve for funds that switch less, but not linearly, as observed in Panels A and C. Funds that switch more aggressively charge significantly higher TERs and are younger. Turnover is generally associated with more aggressive switching, confirming our measure of style switching. Finally, TNA is lower for funds that switch more aggressively.[18] These results are consistent over the different measures for switching.

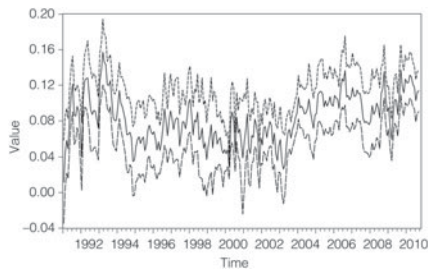
FIGURE 6

Average Conditional Exposures

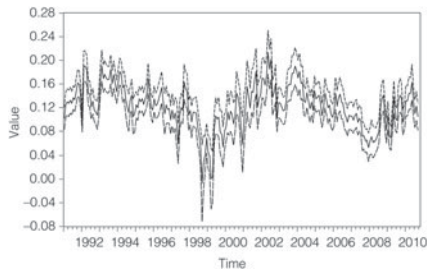
Figure 6 presents the cross-sectional mean and its 95% confidence bounds of the conditional exposures to the four benchmark portfolios, $w_{it}\beta_i^k$. The figures are split up in four graphs: Graph A, the funds that apply momentum in the book-to-market dimension and momentum in the size dimension; Graph B, momentum in book-to-market and contrarian in size; Graph C, contrarian in book-to-market and momentum in size; and Graph D, contrarian in both dimensions. Each graph is again divided into four subgraphs representing each of the four benchmark portfolios.

Graph A. Size Momentum–Value Momentum

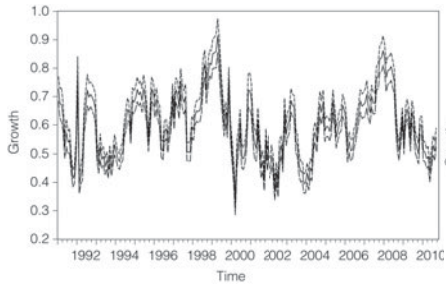
Graph A1. Large Value



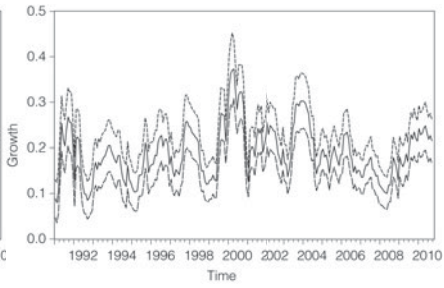
Graph A2. Small Value



Graph A3. Large Growth



Graph A4. Small Growth



(continued on next page)

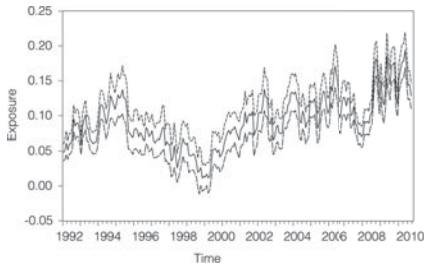
[18]The second decile results are affected by a single extremely large fund.

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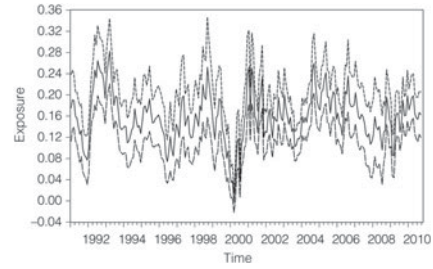
FIGURE 6 (continued)
Average Conditional Exposures

Graph B. Size Contrarian–Value Momentum

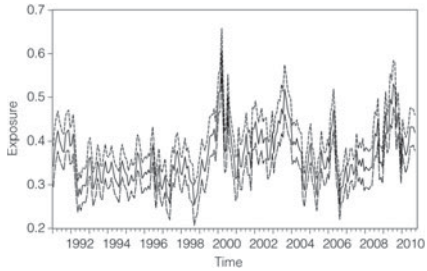
Graph B1. Large Value



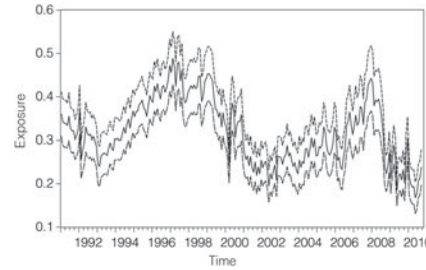
Graph B2. Small Value



Graph B3. Large Growth

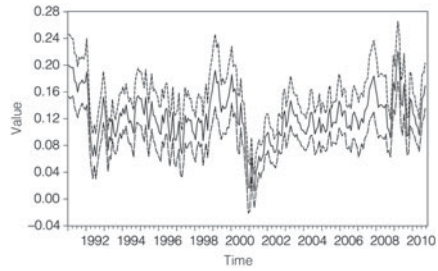


Graph B4. Small Growth

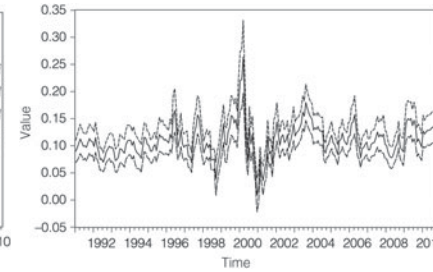


Graph C. Size Momentum–Contrarian

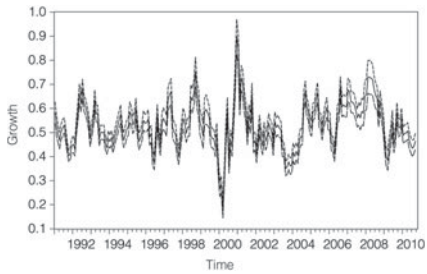
Graph C1. Large Value



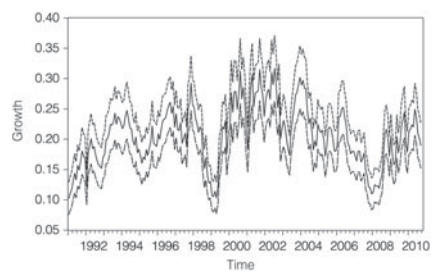
Graph C2. Small Value



Graph C3. Large Growth



Graph C4. Small Growth



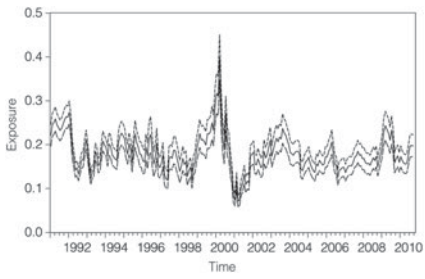
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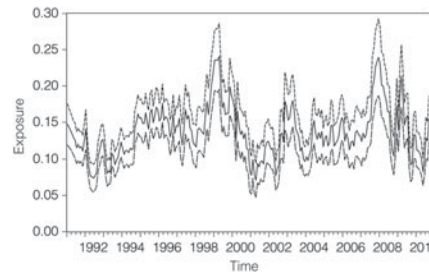
FIGURE 6 (continued)
Average Conditional Exposures

Graph D. Size Contrarian–Value Contrarian

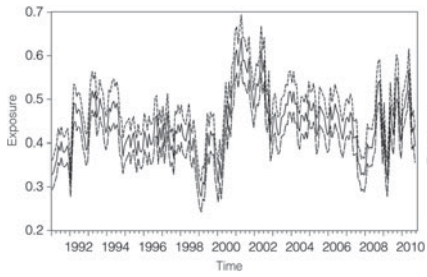
Graph D1. Large Value



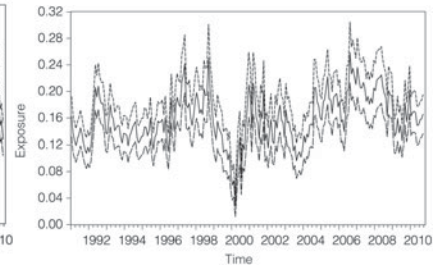
Graph D2. Small Value



Graph D3. Large Growth



Graph D4. Small Growth



Next, we run a cross-sectional regression of the absolute style-switching parameters on several fund characteristics; that is,

$$(9) \qquad |\gamma_i| = \beta_0 + \beta_1 \ln(\text{AGE}_i) + \beta_2 \ln(\text{TNA}_i) + \beta_3 \text{TURNOVER}_i + \beta_4 \text{TER}_i + \beta_5 \text{LOOKBACK}_i + \text{STYLE_DUMMIES}_i + \varepsilon_i,$$

where $\ln(\text{AGE}_i)$ is the natural logarithm median age of the fund, $\ln(\text{TNA}_i)$ is the natural logarithm of the beginning of period size of the fund,[19] TURNOVER_i is the median share turnover of the fund, TER_i is the total expense ratio of the fund, LOOKBACK_i is the lookback period used to estimate γ, and STYLE_DUMMIES_i are dummy variables to control for the style of fund i.

Table 7 presents the results for equation (9) using the different γ's (i.e., $|\gamma^{\text{SINGLE}}|$, $|\gamma^{\text{BM}}|$, and $|\gamma^{\text{SIZE}}|$) and report White-corrected t-statistics in parentheses.[20] Columns 1–3 shows the results for $|\gamma^{\text{SINGLE}}|$. We find a significantly positive relation with TER, suggesting that aggressive switchers have higher TERs. We also find a significantly negative relation with age, suggesting that older funds tend to switch less aggressively. There is also a significantly negative relation with LOOKBACK, suggesting that more aggressive switching occurs with shorter lookback periods.

[19]We include beginning of period TNA of the funds instead of average fund size to avoid endogeneity problems.

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

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TABLE 6

Relation between Style Switching and Fund Characteristics

Table 6 presents the univariate relations between the absolute value of the intensity of choice parameter $|\gamma|$ and several fund characteristics. We sort funds on their switching and create decile portfolios. Panel A represents the single-switching model (equations (5) and (6)). Panels B and C represent the absolute values of the style-switching coefficients in the double-switching model (equations (7) and (8)). LOOKBACK is the fund's optimal lookback period j^*; α^{CAPM}, α^{F3}, and α^{F4} are the CAPM, 3-factor, and 4-factor alpha, respectively; TER_i is the total expense ratio of the fund; AGE_i is the age of the fund; $TURNOVER_i$ is the median share turnover of the fund; and TNA_i is the beginning of period size of the fund. High − Low represents the test of equal means between the 1st and 10th portfolio, and *p*-values are reported below in parentheses.

	$\|\gamma\|$	LOOKBACK	α^{CAPM}	α^{F3}	α^{F4}	TER	AGE	TURNOVER	TNA
Panel A. Single Switching									
1 (High)	0.095	5.293	−0.333	−0.448	−0.425	0.015	11.24	0.903	31.79
2	0.029	5.266	−0.367	−0.472	−0.427	0.014	14.33	0.876	126.06
3	0.018	5.165	−0.407	−0.484	−0.470	0.015	13.63	1.159	40.55
4	0.013	5.846	−0.413	−0.471	−0.448	0.015	13.93	0.926	26.74
5	0.010	5.963	−0.435	−0.460	−0.444	0.014	13.66	0.904	34.38
6	0.008	5.594	−0.400	−0.402	−0.392	0.015	13.25	0.720	27.20
7	0.006	6.064	−0.347	−0.336	−0.321	0.014	13.88	0.718	41.96
8	0.005	7.367	−0.346	−0.363	−0.322	0.014	15.10	0.771	58.98
9	0.004	7.340	−0.321	−0.344	−0.330	0.014	13.98	0.722	50.98
10 (Low)	0.002	8.277	−0.327	−0.331	−0.320	0.013	14.79	0.693	52.48
High − Low	0.093	−2.984	−0.010	−0.118	−0.105	0.002	−3.55	0.209	−20.69
	(0.000)	(0.000)	(0.869)	(0.001)	(0.001)	(0.000)	(0.000)	(0.028)	(0.089)
Panel B. Double Switching: Value									
1 (High)	0.144	3.320	−0.440	−0.528	−0.471	0.015	11.22	0.867	30.269
2	0.051	4.580	−0.400	−0.510	−0.451	0.014	13.85	0.780	40.796
3	0.035	4.667	−0.381	−0.484	−0.442	0.014	14.64	0.725	45.864
4	0.025	5.006	−0.364	−0.459	−0.424	0.013	14.26	0.741	33.774
5	0.018	5.685	−0.326	−0.425	−0.400	0.013	15.55	0.791	66.862
6	0.013	6.221	−0.373	−0.439	−0.415	0.014	14.29	0.798	62.925
7	0.009	6.392	−0.374	−0.376	−0.386	0.014	13.32	0.921	46.703
8	0.006	6.894	−0.339	−0.301	−0.307	0.014	14.47	0.884	34.201
9	0.004	6.906	−0.375	−0.327	−0.332	0.014	15.90	0.920	118.80
10 (Low)	0.002	7.260	−0.277	−0.246	−0.238	0.014	14.95	0.903	37.151
High − Low	0.142	−3.939	−0.163	−0.283	−0.234	0.001	−3.73	−0.036	−6.882
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.021)	(0.000)	(0.770)	(0.316)
Panel C. Double Switching: Size									
1 (High)	0.193	6.077	−0.319	−0.396	−0.387	0.015	10.25	1.237	26.67
2	0.060	5.680	−0.297	−0.405	−0.385	0.015	12.44	0.908	32.52
3	0.036	6.250	−0.324	−0.398	−0.390	0.015	13.46	0.887	49.91
4	0.025	6.249	−0.392	−0.468	−0.441	0.0150	13.08	0.894	37.31
5	0.018	6.249	−0.399	−0.432	−0.403	0.014	14.84	0.884	41.34
6	0.013	6.674	−0.394	−0.439	−0.410	0.014	16.76	0.791	51.04
7	0.009	6.735	−0.418	−0.436	−0.407	0.014	17.09	0.739	47.30
8	0.007	6.844	−0.365	−0.376	−0.353	0.014	15.57	0.790	59.59
9	0.004	6.834	−0.382	−0.399	−0.367	0.012	15.02	0.671	105.27
10 (Low)	0.002	7.055	−0.359	−0.347	−0.323	0.012	13.92	0.528	66.57
High − Low	0.191	−0.978	0.040	−0.049	−0.065	0.003	3.67	0.709	−39.90
	(0.000)	(0.015)	(0.312)	(0.209)	(0.069)	(0.000)	(0.000)	(0.000)	(0.018)

To assess whether positive or negative feedback trading is affected by specific fund characteristics, we separate $|\gamma^{SINGLE}|$ into positive and negative values. We note that TER is insignificant for positive feedback traders, but remains significant for negative feedback traders. Age remains significantly negative for both positive and negative feedback traders. Finally, the significant relation between switching behavior and lookback is driven by negative feedback traders, who switch more aggressively based on shorter lookback periods.

In columns 4–6 of Table 7, we report the results for $|\gamma^{BM}|$. Our results show that switching in the value dimension is positively related to TER. We also note significantly negative relations with age and lookback. When splitting the

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TABLE 7

Relation between Style Switching and Fund Characteristics

Table 7 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)); $\ln(AGE_i)$ is the natural logarithm of the age of the fund; $\ln(TNA_i)$ is the natural logarithm 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). White-corrected *t*-statistics are reported in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

	Single Switching			Double Switching					
	$\|\gamma^{SINGLE}\|$			$\|\gamma^{BM}\|$			$\|\gamma^{SIZE}\|$		
	ALL	POS	NEG	ALL	POS	NEG	ALL	POS	NEG
TER_i	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)
$\ln(AGE_i)$	−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)
$\ln(TNA_i)$	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)
$TURNOVER_i$	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)
$LOOKBACK_i$	−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)
$STYLE_DUMMIES_i$	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
No. of obs.	1,878	838	1,040	1,807	796	1,011	1,807	901	906

switching parameter into positive and negative feedback trading, TER is related only to positive feedback trading. The negative relations of $|\gamma^{BM}|$ with age and lookback are observed in both positive and negative feedback trading.

Columns 7–9 of Table 7 report the results for $|\gamma^{SIZE}|$. We observe that $|\gamma^{SIZE}|$ has a significantly negative relation with age (i.e., older funds switch less aggressively in the size dimension). We further find a significant positive relation with turnover, which suggests that more aggressive switchers have a higher portfolio turnover. When splitting $|\gamma^{SIZE}|$ into positive and negative feedback trading, we find that the relation between $|\gamma^{SIZE}|$ and age is driven by negative feedback trading funds. The relation between turnover and $|\gamma^{SIZE}|$ is driven by the positive feedback trading funds. We observe a significant negative relation between lookback and positive feedback trading, suggesting that fund managers that follow a momentum strategy in the size dimension trade more aggressively with shorter lookback periods.

VI. Style-Based Feedback Trading, Outperformance, and Fund Flows

We next address whether style-based feedback trading is related to outperformance, by computing Jensen's α for each fund and use these α's in the following cross-sectional regression:

$$\begin{aligned}(10)\qquad \alpha_i \;=\; & c + \beta_1\gamma_i^{+} + \beta_2\gamma_i^{+} \times \text{LOOKBACK}_i + \beta_3\gamma_i^{-} \\ & + \beta_4\gamma_i^{-} \times \text{LOOKBACK}_i + \text{FUND_CONTROLS}_i \\ & + \text{STYLE_DUMMIES}_i + \varepsilon_i,\end{aligned}$$

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where α_i is the outperformance measure based on either the capital asset pricing model (CAPM), the Fama–French (1993) 3-factor model, or the Carhart (1997) 4-factor model, and γ_i^+ and γ_i^- are the style-switching parameters for positive and negative feedback trading, respectively. We include an interaction term between γ and LOOKBACK, because different trading strategies may work better for different lookback periods; that is, positive feedback (momentum) trading may work better for shorter lookback periods, whereas negative feedback (contrarian) trading may work better for longer lookback periods. FUND_CONTROLS$_i$ account for fund characteristics shown to affect outperformance, and STYLE_DUMMIES$_i$ are dummy variables to control for the investment style of fund *i*.

In Table 8, we report the results for equation (10). Columns 1–3 assess the relation between the single-switching parameter and the alpha of a fund and show that positive feedback trading yields significant outperformance in the 3- and 4-factor models. The coefficient on the interaction term of positive feedback trading and the lookback period is negative, suggesting that the outperformance obtained from positive feedback trading decreases as the lookback period increases. These results are consistent with Grinblatt et al. (1995), who find that momentum trading yields significantly higher performance. The effect of negative feedback trading has the opposite pattern; it causes losses in the short run shown by the positive significant coefficient for γ^-. For longer lookback periods, the negative effect decreases, but not significantly so. Additionally, we find a negative relation

TABLE 8

Risk-Adjusted Performance and Style Switching

Table 8 displays the estimation results of equation (10). α^{CAPM}, α^{F3}, and α^{F4} are the CAPM, 3-factor, and 4-factor alpha, respectively; γ^+ and γ^- are the style-switching parameters for positive feedback trading and negative feedback trading, respectively. LOOKBACK is the optimal lookback period *j**, ln(AGE) is the natural logarithm of the age of the fund, ln(TNA) is the natural logarithm of the beginning of the period size of the fund, TURNOVER is the median share turnover of the fund, and TER 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. * and ** indicate significance at the 5% and 1% levels, respectively.

	γ^{SINGLE}			γ^{BM}			γ^{SIZE}		
	α^{CAPM}	α^{F3}	α^{F4}	α^{CAPM}	α^{F3}	α^{F4}	α^{CAPM}	α^{F3}	α^{F4}
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^+ × LOOKBACK	−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^- × LOOKBACK	−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)
LOOKBACK	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)
ln(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)
ln(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
Adj. R^2	0.073	0.112	0.091	0.100	0.132	0.088	0.073	0.111	0.082

between α and age, fund size, turnover, and TER. These results are consistent with the literature (see, e.g., Carhart (1997)).

In columns 4–9 of Table 8, we report the results for the switching in the value and size dimensions, respectively. For switching in the value dimension, we find insignificant results for the positive feedback trading rules, but a significantly negative relation between outperformance and negative feedback. For the size dimension, we find that a longer lookback period leads to higher performance, irrespective of the sign of feedback trading.

Finally, we consider whether style-based feedback trading affects fund flows. Barberis and Shleifer (2003) argue that fund managers might chase style returns, because it is an investment strategy that is relatively easy to sell to (retail) investors. To test this hypothesis, we estimate the following equation:

$$\begin{aligned}(11)\qquad \text{FLOWS}_i \;=\; & c + \beta_1\gamma_i^{+} + \beta_2\gamma_i^{+} \times \text{LOOKBACK}_i + \beta_3\gamma_i^{-} \\ & + \beta_4\gamma_i^{-} \times \text{LOOKBACK}_i + \beta_5 \times \text{LOOKBACK}_i \\ & + \text{FUND_CONTROLS}_i + \text{STYLE_DUMMIES}_i + \varepsilon_i,\end{aligned}$$

in which FLOWS_i is the median net inflow into fund i.

The results for equation (11) in Table 9 show that there is no relation between switching and fund flows. Thus, we conclude that switching does not affect

TABLE 9

Fund Flows and Style Switching

Table 9 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. LOOKBACK is the optimal lookback period j^*; ALPHA 4FF is the alpha of a Carhart (1997) 4-factor model; ln(AGE) is the natural logarithm of the age of the fund; ln(TNA) is the natural logarithm of the beginning of the period size of the fund; TURNOVER 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). White-corrected t-statistics are reported in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

	γ^{SINGLE}	γ^{BM}	γ^{SIZE}
γ^{+}	2.675	−3.547	−0.921
	(0.952)	(−1.077)	(−0.221)
$\gamma^{+} \times$ LOOKBACK	−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)
$\gamma^{-} \times$ LOOKBACK	−1.164	−0.205	0.937
	(−0.727)	(−0.260)	(1.944)
LOOKBACK	−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)
ln(AGE)	−0.547	−0.491	−0.493
	(−1.586)	(−1.414)	(−1.415)
ln(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
Adj. R^2	0.058	0.059	0.058

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fund flows. The control variables are consistent with the literature; flow is positively related to performance, whereas flow is inversely related to TER.

VII. Conclusions

This paper seeks empirical evidence for the style investing model proposed by Barberis and Shleifer (2003). Using a sample of U.S. 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). Value (growth) funds have a higher tendency to be negative (positive) feedback traders. Switching seems to occur predominantly between the value and growth styles and less between the small- and large-cap styles. Funds with higher total expense ratios and younger funds have a higher propensity to switch. 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. Applying these rules "incorrectly," such as long-term momentum and short-term contrarian trading, reduces performance.

Appendix. Robustness Analysis

Table 5 of our paper reports the percentage of funds for which we find significant switching, measured by a significant increase in the likelihood function of the switching model versus the nonswitching model. To examine the statistical power of these results, we perform a robustness test of our classification of switching. We do this by using a procedure similar to Blackburn et al. (2014). In their setting, they scramble return signals to determine whether traders are classified in the same way if return signals are scrambled. We implement this procedure in the following way. First, we estimate the switching model and obtain residuals from that model. We then randomly shuffle these residuals and benchmark returns and generate pseudo-returns for each fund under the null hypothesis of no switching. We then estimate the switching model based on the pseudo-returns and collect the LR statistic. We repeat this process 1,000 times for each fund, to obtain an empirical distribution of the LR statistic under the null of no switching. From these bootstrapped values, we obtain the 5% critical value, against which we compare the LR statistic obtained from the real data.

In Table A1, we present the results for this robustness analysis, where we report the percentage of funds for which we find significant switching at the 5% level bootstrapped critical values. Overall, when using the bootstrapped critical values, the number of funds for which we find significant switching decreases. For the single-switching case, we find evidence of about 38% of funds engaging in switching behavior (compared with 53% reported in Table 5, which relies on critical values obtained from a χ^2 distribution). For the double-switching models, we document significant switching for 68% of the funds (compared with 77% reported in Table 5).

Although the percentage of funds for which we find switching is lower when using the bootstrapped critical values, the observed patterns largely remain. In the single-switching case for all size groups, we observe that for the mid- and multi-cap funds, there is significantly more positive feedback trading for growth funds relative to value funds, while at the same time, we observe significantly more negative feedback trading in all value funds compared with growth funds. For the switching in the value dimension, there is significantly more negative feedback trading than positive feedback trading, except for small-cap funds. For the switching in the size dimension, we observe more positive feedback

TABLE A1

Percentage of Switching Funds (based on bootstrapped critical values)

Table A1 presents the percentage of funds for which we find significant switching. Specifically, we give the percentage of funds for which the likelihood ratio exceeds the empirical critical value at the 5% level based on 1,000 bootstrap replications under the null hypothesis of no switching. Panel A presents results of the single-switching model versus the static model; Panel B presents the results of the double-switching model versus the static model. We split results into positive and negative feedback trading and report the difference between positive and negative feedback trading in the row labeled POS − NEG. We test for the significance of this difference using a χ^2 statistic. We also compute the difference in style switching between the Value and Growth styles and report these differences in the columns labeled V − G. We test for the significance of this difference using a *t*-test. * and ** indicate significance at the 5% and 1% levels, respectively.

	ALL	LCVE	LCCE	LCGE	V − G	MCVE	MCCE	MCGE	V − G	MLVE	MLCE	MLGE	V − G	SCVE	SCCE	SCGE	V − G
Panel A. Single γ Model																	
Total	37.84	34.88	37.50	36.25	−1.37	48.78	33.67	35.59	13.19	41.53	40.66	31.51	10.01	34.17	37.30	40.71%	−6.54
POS γ	15.29	6.98	11.03	17.50	−10.52*	10.98	9.18	23.73	−12.75*	9.29	21.99	25.34	−16.05**	1.67	11.91	25.66%	−23.99**
NEG γ	22.55	27.91	26.47	18.75	9.16	37.81	24.49	11.86	25.95**	32.24	18.67	6.16	26.08**	32.50	25.40	15.04%	17.46**
POS − NEG	−7.26**	−20.93**	−15.44**	−1.25		−26.83**	−15.31**	11.87**		−22.95**	3.32	19.18**		−30.83**	−13.49**	10.62	
Panel B. Twin Styles																	
Panel B1. Only Value Switching																	
Total	14.63	12.79	24.26	12.50	0.29	20.73	10.20	6.78	13.95**	18.85	24.07	8.90	9.95**	4.17	13.49	6.20	−2.03
POS γ	3.58	1.16	6.62	6.25	−5.09	4.88	2.04	3.39	1.49	2.62	4.98	2.06	0.12	0.83	3.97	3.54	−2.71
NEG γ	11.05	11.63	17.65	6.25	5.38	15.85	8.16	3.39	12.46**	16.23	19.09	6.85	9.38**	3.33	9.52	2.66	0.67
POS − NEG	−7.47**	−10.47**	−11.03**	0.00		−10.97**	−9.18**	0.00		−13.61**	−14.44**	−4.79*		−2.50	−5.55	0.88	
Panel B2. Only Size Switching																	
Total	26.59	24.42	19.12	15.00	9.42	23.17	21.43	37.29	−14.12*	20.94	21.99	35.62	−14.68**	36.67	23.02	42.48	−5.81
POS γ	14.18	14.12	8.09	6.25	7.87	6.10	10.20	27.12	−21.02**	14.66	9.54	28.77	−14.11**	1.67	10.32	30.97	−29.30**
NEG γ	12.41	10.30	11.03	8.75	1.55	17.07	11.22	10.17	6.90	6.28	12.4	6.85	−0.57	35.00	12.70	11.50	23.50**
POS − NEG	1.77	−3.82	−2.94	−2.50		−10.97**	−1.02	16.95**		8.38**	−2.91	21.92**		−33.33**	−2.38	19.47**	
Panel B3. Double Switching																	
Total	26.74	26.74	16.18	35.00		31.71	25.51	32.20		27.23	24.90	22.60		35.00	23.02	29.46	
POS SIZE/POS BM	5.73	5.88	1.47	7.50		3.66	5.10	8.48		4.71	6.64	10.27		2.5	2.38	9.82	
POS SIZE/NEG BM	6.19	0.00	0.74	10.00		7.32	4.08	10.17		5.24	4.56	4.80		14.17	4.76	11.61	
NEG SIZE/POS BM	6.38	11.77	4.41	5.00		7.32	10.20	9.32		8.90	6.22	2.74		3.33	3.97	5.36	
NEG SIZE/NEG BM	8.46	9.41	9.56	12.50		13.42	6.12	4.24		8.38	7.47	4.80		15.00	11.91	2.68	
Panel B4. Total																	
Total	67.96	63.953	59.56	62.50	1.45	75.61	57.14	76.27	−0.66	67.02	70.95	67.12	−0.10	75.83	59.52	78.14	−2.30

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trading for growth than for value funds (except for large-cap funds) and a significantly higher proportion of negative feedback traders (compared with positive feedback traders) in value funds (except for large-cap funds). Conversely, there is a significantly higher proportion of positive feedback traders relative to negative feedback traders in growth funds (again except for large-cap funds). For the twin style double-switching model, the results are again mixed.

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