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Style Investing and Institutional Investors

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Abstract

This paper explores the importance and price implications of style investing by institutional investors in the stock market. To analyze styles, we assign stocks to deciles or segments across three style dimensions: size, value/growth, and sector. We find strong evidence that institutional investors reallocate across style groupings more intensively than across random stock groupings. In addition, we show that own segment style inflows and returns positively forecast future stock returns, while distant segment style inflows and returns forecast negatively. We argue that behavioral theories play a role in explaining these results.

I. Introduction

It is widely believed that institutional investors use concepts of style to characterize their portfolios and patterns of trade.[1] Popular style categories (e.g., technology stocks, growth stocks, and cyclical stocks) appear important enough to merit the creation of explicit investing mandates and to form the basis of asset allocation by many equity investors. To economize on the number of things to track, investors are often thought to treat stocks as combinations of a small number of style "factors" rather than as independent entities.

If investors use these factors, then they will formulate views and reallocation decisions across large versus small cap stocks, technology versus nontechnology stocks, value versus growth stocks, etc. Such style reallocations should occur with more intensity than reallocations across stocks grouped randomly. Furthermore, style-level demand shocks by a very large group of investors might be expected to have an important impact on prices and expected returns, as other investors would require incentives to skew their portfolio holdings to accommodate them. Style is thus a fertile place to search for evidence of demand shocks when an important investor group is buying.

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[1]See, for example, "Curtain Coming Down on the Sensational Small-Cap Show," *The Financial Times*, August 3, 2006, and "Smart Money Stock Screen/Bargain Growth," *The Wall Street Journal*, May 18, 2006.

Naturally, investor buying could be based on anticipated fundamentals or sentiment. If style categories mirror differences in fundamental exposures, changes in investor demand for styles may reflect fundamental information. As in Kyle (1985), a group of investors buys securities from others when they anticipate positive fundamental information, given current prices.[2] Alternatively, as in Delong, Shleifer, Summers, and Waldmann (1990) and Barberis and Shleifer (2003), noise trader buying is motivated purely by changes in sentiment. Under either interpretation, the buying drives up contemporaneous prices. Both interpretations also suggest that rationally expected returns rise, at least initially, if the buying is expected to persist.[3]

There are, however, two main differences in the empirical predictions of these paradigms. First, price changes should be more permanent if fundamental information is responsible and more transitory if sentiment is responsible. At some horizon, rationally expected returns must become negative under the sentiment story, since eventually, prices converge in expectation back to fundamental values. Second, in the Barberis and Shleifer (2003) model, sentiment affects relative demand, so that a shift toward positive sentiment for a particular style segment not only raises the price of that segment but also lowers the price of distant[4] style segments. By contrast, an improvement in a segment's fundamentals does not usually reduce the price of distant style segments, unless their fundamentals are negatively correlated, something that is rarely observed.

In this paper, we explore two main questions about style-level trading by institutional investors. First, is style trading statistically and economically important? Second, do style-level flows impact future style prices? If they do, is the impact more in keeping with the fundamental-or sentiment-driven story? In this effort, we examine three style dimensions: small/large, value/growth, and sector/industry. To measure institutional flows, we use hitherto unavailable aggregated data from State Street Corporation, collected from its role as fiduciary in tracking about $9 trillion in liquid securities managed by institutional investors. The advantage of the data is that they record daily institutional flows during a time when such aggregated information was not available to any investor.

To preview our results, we find evidence of style-level trading by institutions in all style dimensions that we examine. Year by year,[5] and in every style dimension, institutions trade styles more intensively than they do randomly-generated groupings built to mimic style deciles. Such style-based reallocations cannot be explained by institutional investors' long-term preferences for large stocks (Gompers and Metrick (2001)) or by their reallocations between loser and winner

[2]Brennan and Cao (1997) provide a model in which investor purchases are correlated with the public release of information rather than private anticipation of information as in Kyle (1985).

[3]In the Kyle (1985) model, informed-investor flows exhibit conditional and positive serial correlation, as these investors maximize profits by allowing their information to enter slowly into market prices. In the Barberis and Shleifer (2003) model, noise-trader flows exhibit positive feedback, which directly induces a source of positive serial correlation to their flows. In both contexts, persistence in flow generates conditional predictability in return, which in the short run is extrapolative.

[4]Distant style segments are style segments far apart along the style spectrum (i.e., extreme value vs. extreme growth).

[5]Our sample period spans January 1995 to December 2003.

stocks (Jegadeesh and Titman (1993)). In addition, there is evidence of strong negative correlation between the net flows into distant style segments (e.g., extreme value vs. extreme growth). This suggests that style trading is well characterized by the rotation of institutional funds from one style extreme (e.g., value) toward the opposite extreme (e.g., growth).

Going further, we find that own-style segment returns and flows forecast individual stock returns positively at weekly horizons. This is true even after conditioning on individual company returns, flows, and characteristics such as size, book-to-market equity, and return on equity. We also find that returns and flows into *distant* style segments negatively forecast individual stock returns. For example, a small-cap stock's excess return is predicted negatively by returns and flows into the largest-cap stocks, holding constant small-cap return and flows (as well as that stock's own return and flow). Like inflows into own-segment style flows, outflows from distant style segments forecast positively individual stock returns.[6]

To further distinguish from the fundamentals-driven story, we apply the Campbell (1991) return decomposition, which divides stock returns into a permanent cash flow component and a temporary expected return component. Then, we examine the effects on stock returns of shocks to style variables in the absence of any cash flow news shock. The resultant impulse response functions indicate that our prior findings are driven at least in part by the sentiment-based story. Style returns and flows predict transitory price components, and these effects fully dissipate after 400 to 500 weeks.

The fundamentals-only story also seems weak for explaining the forecasts of returns by distant-segment flows. It seems reasonable that institutional managers might have superior information about future changes in style-segment fundamentals and therefore tend to buy segment stocks before they appreciate. However, we find that, holding constant own-segment inflows, simultaneous inflows into distant style segments reduce future own-segment appreciation. It is hard to rationalize this under the fundamentals story, which does not provide any reason why distant-segment inflows (based on distant-segment fundamentals) should negatively impact own-segment expected return, given own-segment inflows. By contrast, the behavioral view fits the data better—it envisions *relative* segment flow as representing sentiment. Under this view, distant-segment inflows can negatively impact own-segment expected returns.

Our results challenge the classical finance view that style investing does not matter for prices. In doing so, we build on several themes. Barberis and Shleifer (2003) argue that the interaction of rational arbitrageurs and style switchers creates short-term momentum and long-term reversals in style prices. We show that their theoretical predictions are largely borne out in the data. In addition, we document a unique conjugate or distant style effect. Nofsinger and Sias (1999) and

[6]We explore the own- and distant-segment concepts in a multidimensional framework. We place individual stocks into own-segment style deciles across several style dimensions at once. In addition, for each stock we define distant segments by a conjugate region made up of stocks that do not share any of that stock's multidimensional own-segments. For example, the conjugate style flow for stock x is the flow into stocks that do not belong to the same size segment, value/growth segment, and sector segment as stock x.

Froot, O'Connell, and Seasholes (2001) find evidence that institutional flows into U.S. and international stocks are positively correlated with future own-country returns. We affirm this kind of behavior at the level of style. Gompers and Metrick (2001) report that institutional investors unconditionally prefer large stocks. Our size results qualify this statement by showing that institutional investors have relatively stronger preferences for large stocks when recent large-stock returns have been high relative to small-stock returns. Finally, our sentiment results resonate with those of Baker and Wurgler (2006), who show that when sentiment is high, subsequent annual returns for stocks that are difficult to value (i.e., small stocks, extreme-growth stocks, distressed stocks, and young stocks) are low. Unlike their economy-wide sentiment effect, we document a style-level sentiment effect.

This paper also adds to a small but growing empirical literature on style investing.[7] Kumar (2006) analyzes retail investor data and finds evidence of style-driven trading. Unlike Kumar (2006), we focus on institutional investors, and we actively control for fundamentals so as to isolate any behavioral effects. Moreover, we document a positive *noncontemporaneous* relationship between institutional investor style demand and future stock returns, whereas he only finds a positive *contemporaneous* relationship between retail investor style demand and stock returns (see Kumar (2006), Table VII).[8] Teo and Woo (2004) provide evidence of style-level reversals at annual horizons using Morningstar style data. This paper differs from theirs in three ways. First, they do not investigate whether investors consciously group and trade stocks according to style. We show that institutional trading intensity across style groupings is statistically higher than trading intensity across randomly generated groupings. This forms a meaningful basis for the rest of the analysis. Second, they neither test for nor find a distant style effect that is unique to the style investing story. Third, by examining higher frequency data, we find much stronger evidence of style momentum.

The remainder of the paper is organized as follows: Section II describes the data and style definitions, and Section III examines institutional investor reallocation across style groupings. Section IV explores the relationship between style returns/flows and future stock returns. Robustness tests follow in Section V. Section VI concludes.

II. Data and Style Definitions

A. Flow Data

We track the daily investment flows of a very large group of institutional investors. In aggregate, these investors control approximately \$9 trillion in assets, approximately 15% of the world's liquid securities. The transaction data are from State Street Corporation (SSC) and represent complete fiduciary accounts of all

[7]Other notable work on styles include Barberis, Shleifer, and Wurgler (2005), Chen and De Bondt (2004), Asness, Friedman, Krail, and Liew (2000), and Brown and Goetzmann (1997).

[8]Our results are not necessarily inconsistent with Kumar's (2006), as market makers may take the opposite side of the trade when institutions or retail investors are buying.

equity transactions for the portfolios in which these assets are held. SSC is the world's largest custodian.

In order to measure the flows of this group, we aggregate transaction records covering over 9,000 U.S. stocks over a nine-year period (January 3, 1995 to December 31, 2003). This yields over 5.3 million stock days. In performing the aggregation (encompassing hundreds of millions of transaction-level records), we remove test, accounting, and other nonmarket transaction records.[9] We then aggregate up daily net dollar flows—the difference between dollar purchases and dollar sales—into each stock, and divide by market capitalization[10] so that flows (unless otherwise specified) are measured as a fraction of market capitalization.[11] Table 1 provides summary statistics on the flow data, including, for each year, the number of stocks with flows, the number of stock flow days, and the aggregated (across stocks) absolute daily flow averaged over the year.

To characterize the institutional investors captured by the SSC data, we match by hand (using fund name) the funds in the SSC database with those from the CRSP survivorship bias-free mutual fund database. We focus on the subset of diversified domestic equity mutual funds (excluding balanced and sector funds), and list down the number of matched SSC funds and total number of CRSP funds each year in the two rightmost columns of Table 1. The fund numbers indicate that the SSC database tracks flows from almost half of the funds in the CRSP domestic equity mutual fund database, suggesting that our fund universe is representative of the broader domestic equity fund universe.

We supplement the stock flows with return and stock characteristic data from CRSP and COMPUSTAT. Our analysis covers all ordinary common stocks traded on the NYSE, AMEX, and NASDAQ. Following other studies, we exclude ADRs, SBIs, certificates, unit trusts, REITs, closed-end funds, companies incorporated outside the U.S., and Americus Trusts.

B. Style Definitions

Stock characteristic data are used to define three main style dimensions for domestic stocks: small versus large capitalization, value versus growth, and company sector. Each style dimension is divided into deciles, or style "segments." For these three styles, we sort the same universe of stocks by a different company-specific attribute.

For example, the first style dimension, size, is based on a capitalization sort of the universe, dividing it into ten equal-capitalization portfolios.[12] Size deciles

[9] We also employ a filter that removes a very small percentage of outliers, defined as daily net dollar stock flow observations whose absolute value exceeds 10% of outstanding stock market capitalization.

[10] Market capitalization is calculated each year on June 30 using the algorithm outlined in Fama and French (1992).

[11] The data used here represent a substantial improvement over those in Froot, O'Connell, and Seasholes (2001). For example, our trades are recorded on a trade-date rather than on a settlement-date basis; trades are grouped by stock and country of incorporation rather than by currency of settlement; and individual transaction records have been filtered to remove tests, obvious errors, closed accounts, nonmarket accounting transactions.

[12] Institutional investors trade dramatically less in small stocks, so that for our purposes, equal-capitalization rather than equal-count is a more appropriate method for determining decile breakpoints.

TABLE 1

Summary Statistics: State Street Corporation Daily U.S. Individual Stock Flow

Summary statistics from State Street Corporation's (SSC) custodian flow database. The sample period is from January 1995 to December 2003. The data are filtered to remove test and error transactions, and transactions which contain missing data fields. This flow database represents a substantial improvement over that used in Froot, O'Connell, and Seasholes (2001) as trades are recorded on a trade-date rather than on a settlement-date basis. Aggregated absolute daily SSC flows are absolute daily stock dollar flows aggregated across stocks and averaged over the year/sample period. CRSP funds denote all diversified domestic equity funds in CRSP excluding balanced and sector funds.

Year	Number of Stocks with SSC Flows	Number of SSC Flow Days	Aggregated Absolute Daily SSC Flows (in billions)	Number of SSC Funds with Matches to CRSP	Number of CRSP Funds (domestic equity funds excluding balanced and sector funds)
1995	5,734	450,910	1.76	790	1,884
1996	6,526	559,790	2.25	916	2,126
1997	6,970	625,200	2.96	1,248	2,759
1998	7,015	641,900	3.53	1,375	2,998
1999	6,773	637,070	4.34	1,550	3,321
2000	6,673	696,230	8.41	1,754	3,767
2001	5,506	629,200	10.74	1,993	4,198
2002	4,446	536,490	3.93	2,096	4,453
2003	4,463	542,790	3.58	2,362	5,153
Entire sample period	9,991	5,319,600	4.60	2,476	6,503

are assigned as of July 1 of each year based on the immediately prior June 30 market equity capitalization. The assignment remains in place for the subsequent year, at which point the stock is reassigned based on capitalization at that time. For all style dimensions, decile returns are the value-weighted returns of constituent stocks.

To calculate the second style dimension, value versus growth, we sort based on firms' book-to-market equity (BE/ME) values, again dividing firms into ten equal-capitalization deciles. Assignments are made as of July 1 of year t and remain in place for one year. They are based on book equity in the fiscal year ending in calendar year $t-1$ and market capitalization in December of year $t-1$. Following Fama and French (1992), we use these timing conventions to ensure that accounting variables are known before the sort.

To calculate the third style dimension, sector, we sort into sector deciles based on firm SIC codes as of June 30 using the Fama and French (1997) ten industry portfolio classification. The ten sectors are nondurables, durables, oil, chemicals, manufacturing, telecommunications, utilities, shops, finance, and others. As with the previous style dimensions, firms remain in their assigned sector group until the subsequent June 30.

C. Checks on Style Segment Assignments

To check the robustness of size and value/growth classifications, we compute annual decile transition matrixes. That is, we calculate the probability that a stock belonging to decile i in year t belongs to decile j in year t+1. In results not shown, we find that the transition likelihoods vary considerably between the various style designations. The mean absolute yearly change in decile number for size deciles

Nonetheless all our basic results hold when we follow Fama and French (1993) and use NYSE breakpoints to define the size and book-to-market deciles instead.

is 0.10, and for value/growth deciles it is 1.30. This is a broad range. Yet it is also evident that stocks do not move across deciles in a random fashion. For all style categories, stocks have a higher likelihood of transiting to a decile closer to their current decile than to a decile further away from its current decile. It is also comforting to note that stocks in the extreme deciles demonstrate the highest probability of staying in the same decile in the next year.

We find little scope for concern that annual decile reassignments are importantly endogenous to flows. Specifically, when we estimate univariate OLS regressions stacked across firms with annual change in decile number as the dependent variable and past annual stock flows as the independent variable, we find negligible economic and statistical relationships between the two.

III. Styles and Trading Behavior

If styles are important to the way that investors group stocks, then style-based trading should be pervasive and more systematic across stocks than other idiosyncratic sources of trading. Systematic reallocations might occur because much of the fundamental information investors collect pertains to these styles. Such systematic reallocations within a style could also be due to investor sentiment. Our objective here is to gauge the empirical importance of such systematic forces driving reallocations and then to shed any light possible on the mechanisms behind it.

A. A Statistic to Measure Reallocation Intensity

We first measure the magnitude of institutional trading within each of our four defined styles. To do so, we must define a measure of reallocation intensity. For the style dimensions above, how much do investors move funds across deciles? By comparison, how much do investors trade across randomly defined, but identically-sized, deciles of stocks? A measure of their reallocation intensities across different style dimensions, benchmarked by randomized groupings of stocks, should signal the importance of systematic reallocation factors related to style.

We define our reallocation intensity statistic as the cross-decile standard deviation of excess flow (expressed as a percentage of market capitalization) over and above market flow:

$$\sigma_t^f \equiv \left(\sum_{i=1}^{10} \left(\frac{m_{i,t}}{\sum_i m_{i,t}} \left(\frac{F_{i,t}}{m_{i,t}} - \frac{\sum_i F_{i,t}}{\sum_i m_{i,t}} \right)^2 \right) \right)^{0.5}, \tag{1}$$

where $F_{i,t}$ is the dollar flow into decile i at time t and $m_{i,t}$ is the market capitalization of decile i at time t. Excess flow in decile i is defined as $F_{i,t}/m_{i,t} - \sum_i F_{i,t}/\sum_i m_{i,t}$: the flow into decile i as a percentage of decile i market capitalization, less the current mean flow based on total decile flow relative to total market capitalization. The square of excess flow is then value-weighted by the fraction of total market capitalization in decile i, $m_{i,t}/\sum_i m_{i,t}$. For size and value/growth style spectrums, our deciles use equal market capitalizations, so that $m_{i,t}/\sum_i m_{i,t} = 0.1$. The reallocation intensity statistic is defined such that it is the flow analog of the cross-sectional standard deviation in returns $\sigma_t^r = \left(\sum_{i=1}^{10}\left(\frac{1}{10}\left(r_{i,t} - E_t(r_{i,t})\right)^2\right)\right)^{0.5}$ such that excess flow, $F_{i,t}/m_{i,t} - \sum_i F_{i,t}/\sum_i m_{i,t}$, corresponds to $r_{i,t} - E_t\,(r_{i,t})$.

Stocks can be grouped into the deciles in equation (1) using many different rules. Naturally, we group according to the style dimensions we study. However, this does not tell us how much trading intensity we should expect under the null hypothesis that style trading does not occur. To calculate an expected trading intensity, we perform a Monte Carlo exercise. We group all contemporaneously useable stocks into randomly-formed deciles using a uniform distribution to draw from our sample of stocks without replacement. By doing this 10,000 times independently for each year, we compute 10,000 randomly-formed values of trading intensity. We denote the expectation of these trading intensities $E[\sigma_t^f]$.

Next, we test whether the reallocation intensity for each style dimension is statistically greater than the randomly-generated mean, $\sigma_t^f - E[\sigma_t^f]$, using a simple t-statistic for each day.[13] Panel A of Table 2 reports the results, performed for each year of the sample and for the entire sample for each of the three style dimensions.[14] Panel A of Table 2 shows that all styles are traded statistically more than random groupings of stocks. In order, trading intensities are strongest over the entire sample period in the dimensions of sector, size, and then value/growth. The importance of style-based trading has grown relative to other forms of trading, in that all styles reach their highest level of significance in the last three years of our sample period (i.e., 2001 to 2003).

There may be concerns that the results in Table 2 are mechanically generated by institutional investor long-term preferences for stocks with certain characteristics. For example, Gompers and Metrick (2001) report that institutional investors exhibit a strong preference for large capitalization stocks. The reallocation intensity defined in equation (1) may thus capture both institutional investors' long-term preferences and shifts in style. To abstract from institutional investors' long-term preferences, we modify our definition of reallocation intensity to

$$(2)\quad \sigma_t^{\bar{f}} \equiv \left(\sum_{i=1}^{10}\left(\frac{m_{i,t}}{\sum_i m_{i,t}}\left(\frac{F_{i,t}}{m_{i,t}} - \frac{\sum_i F_{i,t}}{\sum_i m_{i,t}} - E\left(\frac{F_{i,t}}{m_{i,t}} - \frac{\sum_i F_{i,t}}{\sum_i m_{i,t}}\right)\right)^2\right)\right)^{0.5}$$

The expectation term in equation (2) is just the time-series mean of style segment i's excess flow. Then, we redo the Monte Carlo experiment. The results in Panel B of Table 2 indicate that our reallocation intensity results are not simply due to institutional investors' long-term preferences.

While the reallocation intensities based on equation (2) address institutional investors' long-term preferences, they may not address their short-term preferences. In particular, as shown by Carhart (1997), institutions may have preferences for high past return stocks and move funds from loser to winner stocks. Distinguishing style-driven trading from stock momentum trading is crucial to the style

[13]In results not reported, we perform the same analysis using the Wilcoxon signed rank test in place of the t-test and reach similar conclusions.

[14]The t-tests are performed by stacking the daily cross-sections over the full sample period.

TABLE 2

Style Reallocation Intensities

Reported *t*-statistics against the mean of a randomly drawn Monte Carlo reallocation intensity sample. The sample period is from January 1995 to December 2003. For each year and for each style (size, value/growth, and sector) 10,000 random Monte Carlo samples of styles are drawn so that their market capitalizations match those of the actual styles. The reallocation intensity statistics associated with these samples are calculated by looking at the stacked series of excess flows for all styles and for each year. Reallocation intensity is a measure of the cross-decile variation in flows in excess of market flows. Each year, the *t*-statistic is calculated from the daily differences between the actual style reallocation intensity and the mean Monte Carlo reallocation intensity. The same process is also repeated over the entire sample period.

	Style Spectrum		
Year	Size	Value/Growth	Sector
Panel A. Report t-Statistics from Reallocation Intensity (see equation (1))			
1995	17.13	2.43	6.51
1996	7.99	1.21	5.69
1997	7.23	3.61	7.46
1998	3.23	2.07	10.12
1999	0.54	2.21	0.24
2000	6.36	5.69	10.74
2001	4.79	6.15	21.88
2002	11.73	4.19	12.74
2003	17.33	1.92	15.53
Entire sample period	21.59	10.01	29.40
Panel B. Reported t-Statistics from Reallocation Intensity Based on Demeaned Excess Flow (see equation (2))			
1995	9.09	2.57	5.17
1996	3.86	1.12	4.52
1997	3.54	3.18	6.81
1998	6.47	2.45	9.47
1999	1.36	2.94	–0.14
2000	3.34	5.56	10.84
2001	3.32	5.59	22.71
2002	8.49	3.35	14.11
2003	9.01	1.19	15.56
Entire sample period	13.73	9.69	28.63

investing story. To that end, we remove the extreme winner and loser stocks from the sample and redo the reallocation intensity analysis (based on equation (1)). Each month, extreme winner (loser) stocks are defined as the top (bottom) 10% of stocks with the highest (lowest) past 2–12 month returns. We use the same formation period as Carhart (1997) when constructing his factor-mimicking portfolio for one-year momentum in stock returns (i.e., PR1YR). If some sort of trend chasing at the stock level is responsible for most of the reallocations we observe at the style level, then the reallocation intensities should fall dramatically when we remove these extreme past return stocks from the sample. After removing the extreme past return stocks, over the full sample period, the *t*-statistics for the size and value/growth reallocation intensities fall to 16.97 and 7.57, respectively, while that for sectors rises slightly to 32.71. Clearly, the reallocation intensities across style segments for the sample without the extreme winners and losers are still comfortably higher than what is predicted by chance.

B. Characteristics-Based Reallocation Across Style Segments

We can go beyond simple volatility measures in describing the cross-decile patterns of reallocation. Does a given style's reallocation volatility come from investors tending to buy deciles 1, 5, and 10 simultaneously while selling the others? Or does it tend to be based more on a style spectrum whereby deciles 1 and 2 are purchased when deciles 9 and 10 are sold? The idea of style reallocations fits better with the latter pattern—which may plausibly be driven by a single common factor—than with the former. To pursue this, we look at the correlations between the flows of various deciles and the major principal components of style flows.

First, we simply plot the 12-week moving average of excess flow for extreme size and value/growth deciles in Figure 1. The subplots of Figure 1 depict a strong negative correlation between excess flows into the most distant deciles (i.e., smallest size segment versus largest size segment, and lowest book-to-market segment (growth) versus highest book-to-market segment (value)). The strong negative correlation is visually evident throughout the entire nine-year sample.

To confirm this, we report in Table 3 pairwise correlations between weekly excess flows of extreme deciles. The results for size and value/growth style spectrums show large negative correlations for the most distant flow deciles. In addition, the correlations fall almost monotonically as the distance between deciles grows ("distance" is defined here as the difference in rank between decile pairs). Reported Spearman rank correlation coefficients, that test the null hypothesis that the distance and excess flow correlations are independent, corroborate this observation. We note that the correlation coefficient between extreme segment excess flow for size and value/growth are, respectively, −0.22 and −0.24 (all of these are statistically beneath −0.11, the correlation expected ex ante among randomized

FIGURE 1

Institutional Investor Flow into Extreme Size and Value/Growth Segments

The sample period is from January 1995 to December 2003. The top graphic plots the excess flows into the smallest and largest market equity deciles. The bottom graphic plots the excess flows into the lowest and highest book-to-market equity deciles. Excess flow is flow (dollar flow scaled by market capitalization) in excess of market flow at each time period. Twelve-week (one quarter) moving averages of demeaned excess flows are depicted.

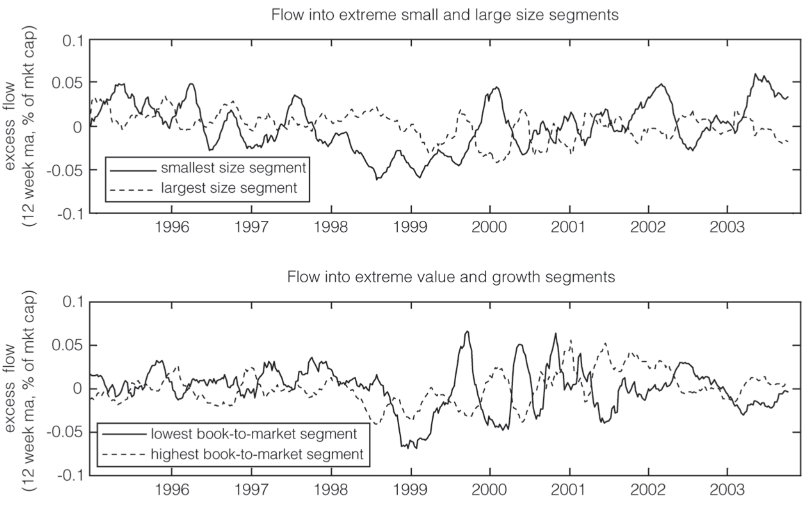


TABLE 3

Flow Correlations Between Style Segments

The sample period is from January 1995 to December 2003. Weekly excess flow correlations between various size (ME) and value/growth (BM) segments Excess flow is flow into a segment in excess of its expected flow given its market cap. Portfolio distance is the difference in rank between portfolios (e.g., the distance between ME1 and ME5 is 4). Correlations are reported for pairs of portfolios with at least 1 extreme portfolio (e.g., ME1, ME10, and BM1). The mean correlations between pairs of a certain distance for each distance are also reported. The *t*-statistics against that of 10,000 Monte Carlo style segment samples, drawn so that their market caps match those of the actual style segments, are in parentheses. * and ** indicate ρ significance at the 5% and 1% levels, respectively.

	Size Segment Correlations			Value/Growth Segment Correlations		
Portfolio Distance	Correlation with ME1	Correlation with ME10	Mean Correlation	Correlation with BM1	Correlation with BM10	Mean Correlation
1	0.21	–0.06	0.00	–0.02	0.20	–0.02
	(5.58)	(0.77)	(1.80)	(1.49)	(5.39)	(1.60)
2	–0.03	–0.10	–0.06	–0.20	0.10	–0.11
	(1.31)	(0.17)	(0.77)	(–1.51)	(3.65)	(0.02)
3	0.04	–0.03	–0.09	–0.14	–0.15	–0.07
	(2.61)	(1.32)	(0.39)	(–0.45)	(–0.62)	(0.60)
4	–0.16	–0.06	–0.11	–0.15	–0.16	–0.12
	(–0.83)	(0.82)	(–0.01)	(–0.73)	(–0.86)	(–0.22)
5	–0.13	–0.25	–0.20	–0.16	0.03	–0.08
	(–0.30)	(–2.43)	(–1.53)	(–0.93)	(2.39)	(0.45)
6	–0.19	–0.25	–0.24	–0.22	–0.19	–0.16
	(–1.44)	(–2.51)	(–2.29)	(–1.85)	(–1.38)	(–0.90)
7	–0.08	–0.15	–0.17	–0.37	–0.11	–0.26
	(0.53)	(–0.67)	(–1.10)	(–4.50)	(–0.01)	(–2.52)
8	–0.11	–0.19	–0.15	–0.16	–0.25	–0.20
	(–0.05)	(–1.39)	(–0.72)	(–0.81)	(–2.39)	(–1.60)
9	–0.22	–0.22	–0.22	–0.24	–0.24	–0.24
	(–1.87)	(–1.87)	(–1.87)	(–2.18)	(–2.18)	(–2.18)
Spearman's ρ	–0.72*	–0.62	–0.80*	–0.67	–0.80*	–0.87**

deciles of firms' excess flows).[15] These results provide further evidence that investors use some version of style dimensions like ours in trading and allocating their portfolios.

For a different look at the importance of multiple factors in explaining the variation in segment flows, we employ principal components. We extract the largest eigenvectors from the covariance matrix of decile flows for each style and estimate the fraction of flow variation explained by each. We then test whether the R^2s are statistically greater than those from the Monte Carlo deciles. The results for the top three principal components are displayed in Table 4. The reported numbers are the adjusted R^2s signed by the correlation coefficient estimates to clarify the direction of the exposure between the principal components and decile flows.

Table 4 suggests that a large portion of interdecile reallocation fits the simple notion of style reallocation: the most extreme deciles have opposite exposures to the most important principal components, while near-extreme deciles have similarly-signed exposures to the nearby extreme. For example, the main principal component for size segment flow loads negatively on the small style segments (ME1 and ME2) and positively on the large style segments (ME9 and ME10), acting as a proxy for style-switching activity along the size spectrum. The first principal component explains 20.27% of the cross-sectional variation in returns. The results are similar for the value/growth style. The main principal component, which explains 27.11% of the cross-sectional variation in returns, loads negatively

[15]The *t*-statistics in Table 3 are against the null hypothesis that the excess flows are random across deciles; under the null, these correlations are all –0.11.

TABLE 4

A Principal Components Analysis of Style Flows

The sample period is January 1995 to December 2003. Principal components analysis is performed on weekly excess flow into size segments (ME) and on weekly excess flow into value/growth segments (BM), separately. Next, the segment flows are regressed individually on the top three principal components and the adjusted R^2s from these regressions are recorded. The numbers presented are the adjusted R^2s signed by the coefficient estimate on the principal components in the above-mentioned regressions. Significance is calculated relative to 10,000 Monte Carlo style segment samples. These samples are drawn so that their market caps match those of the actual style segments. * and ** indicate significance at the 5% and 1% levels, respectively.

	Size			Value/Growth		
Decile	PC1	PC2	PC3	PC1	PC2	PC3
1	−0.58*	0.05	−0.21	−0.98**	0.01	0.00
2	−0.39	0.08	0.19	−0.01	−0.19	−0.33
3	−0.09	0.01	0.27	0.03	−0.09	0.01
4	−0.06	−0.09	−0.03	0.01	−0.22	0.13
5	0.00	−0.45*	0.16	0.02	0.08	−0.57**
6	0.01	0.00	0.00	0.02	−0.05	0.09
7	0.10	−0.03	0.00	0.04	−0.08	0.02
8	0.05	−0.04	−0.17	0.19	0.01	0.00
9	0.10	−0.01	−0.27	0.04	0.34	0.16
10	0.32	0.52**	0.01	0.10	0.46*	0.00
% of cross section explained by principal component	20.27**	15.01	13.35	27.11**	13.73	12.39

on the extreme growth segments (BM1 and BM2) and positively on the extreme value segments (BM9 and BM10).

Naturally, if the deciles were comprised of randomly-assigned firms, we would expect exposures of zero to these factors. In addition, from our Monte Carlo experiment, we find that the first principal component would contribute on average 16.2% of the variation in cross-decile reallocation. The largest principal components in our style flows are therefore larger than that from randomly-assigned deciles. The size of the first principal components and the exposure of extreme deciles to them are further evidence that the size and value/growth styles we identified are traded on by investors.

IV. Styles and Equity Returns

The previous section presented evidence that investors reallocate their portfolios using common definitions of style, and that, to a first approximation, their style reallocations can be summarized as movements driven by a small number of common factors. In order to understand the impact of style attributes (i.e., style flows and returns), we turn to their relationship with stock returns. To begin, we explore the relationship between style attributes and the cross-section of future stock returns. Next, we gauge the economic significance of this relationship by analyzing the returns that can be harvested from simple style momentum-based investment strategies. Finally, we employ a return decomposition to rigorously test for the effects of style attributes on stock returns in the absence of any news on fundamentals and to gauge the transience of the aforementioned relationship.

Following Froot and Ramadorai (2005), we divide the empirical possibilities into three hypotheses. First, that the institutional style flows we observe are uninteresting in that they are not related to any prices at any leads or lags. Fundamentals affect prices, but flows do not, so we call this the "fundamentals-only view." Second, that the flows represent investor reactions to some form of information about long-run or intrinsic value, information that permanently impacts prices. This is called the "strong flow-centric view" to signal an expected positive correlation between flows and fundamental news. And third, that these investor flows do impact prices, but in a transitory, rather than permanent, way. Flows are associated with price *deviations* from long-run or intrinsic values, but not with changes in those values themselves.

This last hypothesis—called the "weak flow-centric view"—is most consistent with sentiment-driven models of trading. These models make a number of specific empirical predictions for style flows and returns: positive contemporaneous correlations between style flows and returns (because style investors take liquidity from the market to satisfy their sentiment-driven demands); positive correlations between previous returns and sentiment-driven flows (hardwired in some models by assuming style investors are trend-chasers); positive correlations between current style flows and future short-horizon returns (driven by the momentum aspects of trend chasing); and zero correlations between current style flows and long-horizon returns (because long-run valuations are ultimately independent of sentiment-driven style demand). Consequently, at long horizons, flows and returns become unrelated: permanent innovations to fundamentals are uncorrelated with sentiment-driven flows but account for virtually all long-horizon return variation. For this to occur, noncontemporaneous correlations between flows and returns must be positive at shorter horizons (to reflect both the momentum and trend chasing features) and negative at longer horizons (to reflect the fact that flow-driven price impacts are transitory).

A. Style Returns/Flows and Future Stock Returns

In this section we explore the relationship between recent style attributes and future stock returns. Under the flow-centric view, over relatively short horizons, nearby style flows and returns should forecast positively stock returns. Moreover, if the institutions trade on *relative* style returns as in the style switching model of Barberis and Shleifer (2003), then distant segment style returns and flows should forecast negatively stock returns as well.[16]

For a given style dimension, we define a stock's nearby-segment as the decile to which that stock is assigned. Consider, for example, a hypothetical stock ZZZ, which is assigned to the first size decile, the second value/growth decile, and the third sector. These deciles are ZZZ's nearby-segments. To construct ZZZ's distant-segment flows and returns, we combine all stocks that are *not* in the union of ZZZ's nearby segments. We call this ZZZ's "conjugate," and it is comprised of all those stocks that are distant in *all three* style dimensions from ZZZ (i.e., the intersection of all stocks *not* in the first size decile, the second value/growth decile, and the third sector).[17]

[16]Teo and Woo (2004) neither explore the effects of distant style segments nor can they investigate the short-term effects of style flows and returns given the quarterly frequency of their data.

[17]To clarify, if a stock is in the second size decile, second value/growth decile, and second sector, it is *not* included in the conjugate of stock ZZZ.

To test for the presence of these style-level momentum and anticipation effects, we estimate a panel regression of the jth stock's excess returns[18] projected on several variables: i) past own-stock excess flows and excess returns (denoted, respectively by $f^{o}_{j,t-\tau}$ and $r^{o}_{j,t-\tau}$); ii) nearby style segment excess flows and returns (denoted, respectively by $f^{n}_{j,t-\tau}$ and $r^{n}_{j,t-\tau}$); and iii) conjugate excess flows and returns (denoted, respectively by $f^{c}_{j,t-\tau}$ and $r^{c}_{j,t-\tau}$). Nearby-segment flows (and returns) are defined for a specific style dimension: size, value/growth, and industry/sector. We denote these as $f^{n,s}_{j,t-\tau}$, $f^{n,v}_{j,t-\tau}$, and $f^{n,i}_{j,t-\tau}$ (and $r^{n,s}_{j,t-\tau}$, $r^{n,v}_{j,t-\tau}$, and $r^{n,i}_{j,t-\tau}$), respectively.

We estimate two versions of the pooled OLS regression using weekly data, the first with a more minimal lag structure:[19]

$$(3)\qquad r_{j,t} = \sum_{x=\{f,r\}} \left(\beta^{o}_{x} x^{o}_{j,t-1} + \sum_{k=\{s,v,i\}} \beta^{n,k}_{x} x^{n,k}_{j,t-1} + \beta^{c}_{x} x^{c}_{j,t-1} \right) + \gamma Z_{j,t-1} + \varepsilon_{j,t},$$

where x represents flow or return, k represents a particular style dimension for nearby segments—s for size, v for value/growth, and i for industry—and $Z_{j,t-1}$ represents three own-firm controls with separate coefficients: book-to-market ratio ($\text{BM}_{j,t-1}$), log market capitalization ($\text{ME}_{j,t-1}$), and return on equity ($\text{ROE}_{j,t-1}$).

The version with more extended lags is given by:

$$(4)\quad r_{j,t} = \sum_{\tau=1}^{12} \sum_{x=\{f,r\}} \left(\beta^{o,\tau}_{x} x^{o}_{j,t-\tau} + \sum_{k=\{s,v,i\}} \beta^{n,k,\tau}_{x} x^{n,k}_{j,t-\tau} + \beta^{c,\tau}_{x} x^{c}_{j,t-\tau} \right) + \gamma Z_{j,t-1} + \varepsilon_{j,t}.$$

For parsimony, the lags employ the following restrictions: subscript $t-1$ represents the one-week lag, and coefficients at lags $t-2$ through $t-4$ (rest of month) and at lags of $t-5$ through $t-12$ (rest of quarter) are restricted to be equal, so that the reported estimates represent average coefficients over that period. The estimated coefficients and t-statistics[20] from the regressions are displayed in Table 5.

The results in Table 5 are broadly consistent with the flow-centric views of style investing. The first lag of nearby-segment returns and flows positively forecast weekly excess returns. The estimates for equation (3), for example, show that a one standard deviation increase in the previous week's nearby size segment return increases expected excess returns by 13.75 basis points. Similarly, a one standard deviation increase in the previous week's nearby size segment flow increases expected excess returns by 5.37 basis points. Similar results obtain for the nearby segments of value/growth and sector.

[18] Excess returns and flows are returns and flows in excess of the value-weighted market return and flow, respectively.

[19] We use stocks with trades on at least 50 days per year every year over the sample period. This ensures the own-flows are well-measured controls. We reestimate the regressions for those firms with at least 100 trading days per year and find results that are qualitatively similar to the baseline case presented below. In response to survivorship concerns, we also redo the analysis on those firms with at least 50 trading days in *any* year. The results are robust to this adjustment as well.

[20] The t-statistics are derived from White (1980) standard errors.

TABLE 5

OLS Firm Fixed-Effects Panel Regressions on Individual Stock Returns

Sample period is from January 1995 to December 2003 and consists of 291,455 firm-weeks. The dependent variable is individual stock return. The independent variables are weekly lags of stock returns and flows, size segment returns and flows, value/growth segment returns and flows, sector segment returns and flows, conjugate returns and flows, as well as stock BE/ME, log ME, and ROE. Flows are net inflows normalized by market equity and are in excess of the U.S. market value-weighted flows. Returns are in excess of the U.S. market value-weighted return. All segment flows and returns are value-weighted. Conjugate flow is the value-weighted flow of all the stocks not in the size segment, not in the value/growth segment, and not in the sector of the stock. Conjugate return is defined analogously. BE/ME is book-to-market equity where book equity is for firm's latest fiscal year ending in year $t-1$ and market equity is measured at the end of year $t-1$. ME is market equity measured in June of year t. ROE is U.S. GAAP return on equity for firm's latest fiscal year ending in year $t-1$. The t-statistics, derived from White (1980) standard errors, are in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

Independent Variables	Equation (3)	Equation (4)		
Coefficient × Std Dev (in basis pts of return)	1 Week Lag	1 Week Lag	2–4 Week Lag	5–12 Week Lag
Stock return	−30.16**	−31.68**	−13.71**	−10.92**
	(−18.90)	(−19.78)	(−9.70)	(−7.64)
Stock flow	−0.05	1.44	−1.63	−4.58**
	(−0.04)	(1.16)	(−1.21)	(−3.56)
Size segment return	13.75**	6.21**	7.87**	3.85**
	(13.32)	(4.91)	(6.08)	(3.45)
Size segment flow	5.37**	2.23	3.13*	3.23**
	(5.09)	(1.89)	(2.43)	(2.68)
Value/growth segment return	4.31**	3.49**	15.17**	6.52**
	(3.75)	(3.03)	(12.75)	(5.10)
Value/growth segment flow	13.18**	11.11**	−4.65**	3.74**
	(10.75)	(8.52)	(−3.53)	(2.84)
Sector segment return	3.79**	2.82*	5.28**	−5.65**
	(3.36)	(2.49)	(4.72)	(−5.14)
Sector segment flow	2.88*	2.29*	5.35**	−0.97
	(2.58)	(1.96)	(4.63)	(−0.92)
Conjugate return	−4.35**	−6.06**	9.97**	−9.38**
	(−3.90)	(−5.35)	(7.82)	(−7.76)
Conjugate flow	−11.13**	−8.44**	−4.62**	4.84**
	(−8.89)	(−6.47)	(−3.74)	(4.12)
Stock BE/ME	17.45**	16.85**		
	(12.34)	(11.66)		
Stock log ME	−18.04**	−20.13**		
	(−15.37)	(−16.30)		
Stock ROE	4.51**	4.44**		
	(3.34)	(3.28)		
Adjusted R^2	0.0067	0.0097		

Consistent with the predictions of the Barberis and Shleifer (2003) model, the first lags of the distant-segment conjugate returns and flows negatively forecast weekly returns. The estimates for equation (3) show that a one standard deviation increase in lagged conjugate returns decreases expected weekly excess returns by 4.35 basis points. Similarly, a one standard deviation increase in lagged conjugate flows decreases expected weekly excess returns by 11.13 basis points.

Estimates of equation (4), which includes parsimonious lag coefficients, lead to similar conclusions. All the coefficients on one-week lags of nearby flows and returns remain positive, while those on conjugate flow and returns remain negative. At longer lags, however, there are signs that the shorter-term effects weaken. The coefficients are more mixed in sign, with some negative coefficients appearing for nearby-segment flows and returns, and with positive coefficients appearing for distant-segment flows and returns. We note that these style effects appear after controlling for own-stock returns, flows, and characteristics (size, book-to-market equity, and profitability). The controls for own-stock characteristics are motivated by the factors reported in Fama and French (1992), Banz (1981), and Haugen and Baker (1996).[21]

Several studies on stock market anomalies have concluded that small stocks are more inefficient than large stocks (Hong, Lim, and Stein (2000), Mitchell and Stafford (2000)). Moreover, one incurs greater transactions cost trading small stocks, and there are concerns that lead lag patterns between large stocks and small stocks (Lo and MacKinlay (1988)) may be driving the high frequency style effects we see in Table 5. Hence, we remove stocks with market capitalization below the NYSE 10th percentile and reestimate the regressions in equations (3) and (4). The results, after removing these small stocks, are almost identical to those in Table 5. Given that State Street Bank's custody clients are mostly large institutions, and that we require sufficient flow observations for inclusion in the panel, most of the stocks easily exceed the size cutoff. Inferences also remain unchanged when we remove stocks with market capitalization below the NYSE 20th percentile. There may be concerns that because we only include up until the first quarterly lag of own-stock returns as controls in the regression (see equation (4)), we may not be adequately accounting for the Jegadeesh and Titman (1993) one-year stock momentum anomaly. Hence, we augment equation (4) with three additional lags of quarterly stock returns (quarterly stock return lagged two quarters, lagged three quarters, and lagged four quarters) and redo the analysis. The results are robust to these additional controls for stock momentum. As a further robustness check and to ensure that extreme data points are not unduly influencing the results, we reestimate the regressions with feasible generalized least squares (FGLS). None of our inferences are sensitive to this change.

The results in Table 5 clearly suggest that institutional investors' style-based anticipation accounts for at least a portion of the style momentum effects. Is there also evidence of style-based positive-feedback trading or trend chasing? To answer this, we rerun the regressions in equations (3) and (4), but with jth-firm flows as the dependent variable. In results not reported, we find statistical evidence of trend chasing at the style level even after controlling for trend chasing at the stock level. That is, controlling for past stock returns and the other variables, nearby style returns forecast positively own-stock flow while distant style returns forecast negatively own-stock flow. Like the distant style segment effect, this is also consistent with the positive feedback style switching model proposed by Barberis and Shleifer (2003).

Having established a positive relationship between short-horizon style flows and returns and future stock returns, it will be interesting and useful to gauge the economic significance of this relationship. To this end, we follow the methodology of Haugen and Baker (1996) and sort stocks each week based on their expected return. The expected returns are estimated via rolling regressions of weekly stock returns on the first weekly lags of size segment returns and flows, value/growth segment returns and flows, sector returns and flows, and conjugate

[21] Fama and French (1992) find that high book-to-market stocks provide higher returns. Banz (1981) documents the existence of the size effect. Haugen and Baker (1996) show that, all else being equal, firms with higher profitability tend to have higher average returns. We follow Haugen and Baker (1996) and use Generally Accepted Accounting Principles (GAAP) ROE instead of clean surplus ROE.

returns and flows, based on the past 52 weeks of data. This is simply a stripped-down version of equation (3) after removing the control variables for stock returns, flows, and characteristics from the RHS. The rolling regressions generate betas that are then used to construct the one week forward expected return forecasts. In results not reported but available upon request, we find that the investment strategy that buys the top 30% of the stocks and shorts the bottom 30% of the stocks based on expected return generates risk-adjusted return in excess of 10% per annum. This is true whether we evaluate performance relative to the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, or the Fama and French (1997) conditional factor model. To further control for stock momentum, we also implement a two-pass sort where we first sort on stock returns and then sort on the style-based expected returns. Relative to the baseline sort, the two-pass sort delivers qualitatively similar results. One concern is that the expected returns are based on the past week's style flows which, at best, are available after a processing lag of a few days. However, even after accommodating for this fact, by either introducing a gap of a week between the formation and evaluation period or by using only past style returns to generate the expected returns, the sort still delivers economically and statistically significant risk-adjusted returns.

B. Return Decomposition

While the evidence in Section IV.A is consistent with both the strong and weak flow-centric views, it remains to discriminate between them. Since the key distinction between the strong and weak flow-centric views is whether flows relate to transitory or permanent return components, one way to test the weak flow-centric view is to search, by trial and error, for style reversal effects at longer horizons using the naïve regression approach of Section IV.A. However, this approach implicitly assumes that the strong and weak flow-centric hypotheses are mutually exclusive. A cleaner and more decisive way of testing the latter would be to first decompose stock return into its permanent and transitory components, and then test the effects of style attributes on the transitory component using a vector autoregression (VAR). By generating the appropriate impulse response functions, one can also pin down the exact horizon at which any reversals occur without resorting to trial and error.

In this effort, we apply Campbell's (1991) return decomposition, dividing stock returns into a permanent "cash flow" component and a temporary "expected return" component:

$$(5) \qquad r_t - E_{t-1} r_t = (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j e_{t+j} - (E_t - E_{t-1}) \sum_{j=0}^{\infty} \rho^j r_{t+j} + \kappa_t,$$

where ρ is the weekly discount rate (set to 0.998 as in Cohen, Gompers, and Voulteenaho (2002)), e_t is the clean surplus accounting ROE in period t, r_t is the return of the stock in period t, and κ_t is the approximation error in period t. The first terms on the right-hand side are, respectively, the permanent cash flow news component of returns and the temporary expected return news component of returns.

Two other papers use this decomposition for purposes similar to ours. Cohen, Gompers, and Vuolteenaho (2002) focus on the flow predictions of returns, finding that institutional investors buy after positive returns generated by permanent innovations but sell subsequent to positive returns generated by transitory return innovations. Froot and Ramadorai (2005) provide a similar decomposition for currency returns and institutional currency flows.

As is standard, we implement the decomposition with a VAR. The state variables are own-stock flow and return, nearby-segment flow and return (for size, value/growth, and sector), conjugate flow and return, and the same own-stock characteristics from the previous regressions. Because the number of coefficients increases with the square of the number of state variables, we use the lag structure of equation (3). We also assume that own-stock flow and return and own-stock characteristic coefficients are zero in the style segment equations, essentially assuming that each stock has only a negligible effect on its segment flow or return.

The VAR system can be summarized with the following notation:

(6) $$z_{i,t} = \Gamma z_{i,t-1} + u_{i,t},$$

where $z_{i,t}$ is a vector of firm-specific state variables describing the firm at time t, and $u_{i,t}$ is an error term that is independent of information available at time $t-1$ and that has covariance matrix of $E[u_t u_t'] = \Sigma$. If we let the first variable in the vector be own-firm excess return, and define $e1' = [1\ 0\ \ldots\ 0]$ and $\lambda' = e1'$ $\rho\Gamma(I-\rho\Gamma)^{-1}$, then as shown by Campbell (1991), the temporary expected return component can be written as $\lambda' u_{i,t}$ and the permanent cash flow component can be written as $(e1' + \lambda')\, u_{i,t}$.

The VAR impulse response allows us to identify how shocks affect expected paths. Specifically, the innovation in cumulative expected future changes $k \geq 1$ periods forward is given by $\Phi(k)u_t$, where

(7) $$\Phi(k)u_t = (\Gamma - \Gamma^{k+1})(I - \Gamma)^{-1}u_t.$$

We pick out cumulated expected changes in any VAR variable by premultiplying by the appropriate selection vector. For example, the innovation in the cumulated expectations of the first variable, stock flows, is given by $e1'\Phi(k)u_t$. Analogously, the innovation in cumulated expectations of the second variable, own-stock return, is given by $e2'\Phi(k)u_t$, where $e2' = [0\ 1\ \ldots\ 0]$. The total impulse response from a shock to stock returns is the sum of the innovation in cumulative expected future returns, $e1'\Phi(k)u_t$, plus the shock itself, $e1'u_t$, or

(8) $$e1'\Psi(k)u_t = e1'(\Phi(k) + I)u_t,$$

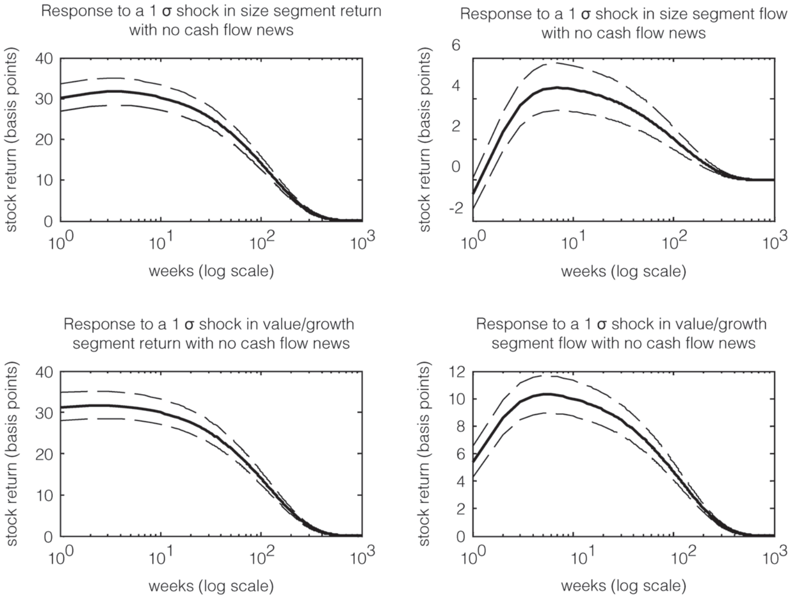
where $\Psi(k) = (\Phi(k) + I)$.

To test the weak flow-centric hypothesis, we examine the impact of style variables on the temporary component of stock return. To do so, we plot the impulse responses of stock returns to style shocks, but allowing for no change in cash flow news. This implies that the unexpected return shock is entirely temporary,

FIGURE 2

Response of Stock Return to One Standard Deviation Shocks in Style Variables with No Cash Flow News.

The sample period is from January 1995 to December 2003. The one standard deviation shock in a variable is induced by setting the corresponding element of VAR error vector to the one standard deviation value. The other elements of the VAR error vector are set to their conditional expectations, conditional on the variable element being equal to its one standard deviation value and cash flow news equals zero. Dashed lines sketched in lighter weight denote ±2 standard error Monte Carlo bounds.



much like the price changes of a zero-coupon default-free bond.[22] The results, displayed in Figures 2 and 3, are consistent with the results from the regressions of Section IV.A. They show that a positive shock to nearby-segment size, value/growth, and sector segment returns and flows leads to increases in the transitory component of stock returns. Furthermore, after a positive shock to nearby segment style flows, stock returns continue to rise beyond the first week, so the impact of style flow shocks on stock returns is persistent. The figures also show that nearby-segment return/flow shocks begin to dissipate after about five weeks, although full elimination requires 400–500 weeks.

Figure 3 reveals that the conjugate return and flow results also agree with the previous regressions. Following a positive shock to either conjugate return or flow, stock returns decrease, even when setting cash flow shocks to zero. This decline requires a long time—about 500 weeks—before it is undone.

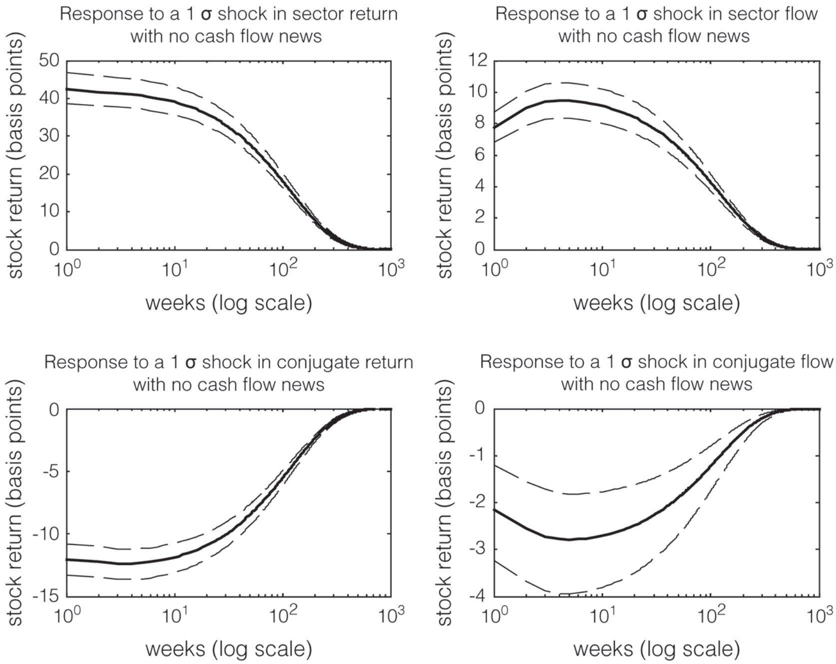
In summary, the results of the return decomposition broadly agree with the previous regression results. In both cases, nearby-segment style flows and returns have a positive effect on stock returns and conjugate style flows, and returns have a

[22]We induce this shock by setting the appropriate element of the VAR error vector to a one standard deviation value, with other elements set to their conditional expectations (i.e., conditional on the style variable element set at its one standard deviation value and the cash flow shock set to zero).

FIGURE 3

Response of Stock Return to One Standard Deviation Stocks in Style/Conjugate Variables with No Cash Flow News

The sample period is from January 1995 to December 2003. The one standard deviation shock in a variable is induced by setting the corresponding element of VAR error vector to the one standard deviation value. The other elements of the VAR error vector are set to their conditional expectations, conditional on the variable element being equal to its one standard deviation value and cash flow news equals zero. Dashed lines sketched in lighter weight denote ±2 standard error Monte Carlo bounds.



negative impact on stock returns. The VAR results are, however, stronger because they imply an effect solely on the transitory component of returns. The results therefore provide evidence of the weak flow-centric hypothesis.

V. Robustness Tests

This section rounds out the empirical discussion with some robustness tests. The robustness tests further control for the correlation between style flows and returns, and for the presence of anomalous industries.

A. Orthogonalizing Flows and Returns

There may be concerns that since flows are highly correlated with returns, the regressions in Table 5 may not be accurately measuring the incremental explanatory power of flows. Even though we include both return and flow lags in the equation (3) and (4) regressions, the intimate relationship between returns and

TABLE 6

OLS Firm Fixed-Effects Panel Regressions with Orthogonalized Flows and Returns

Sample period is from January 1995 to December 2003 and consists of 291,455 firm-weeks. The dependent variable is individual stock return. The independent variables are weekly lags of stock returns and flows, size segment returns and flows, value/growth segment returns and flows, sector segment returns and flows, conjugate returns and flows, as well as stock BE/ME, log ME, and ROE. Flows are net inflows normalized by market equity and are excess of the U.S. market flows. Returns are excess of the US market. All segment flows and returns are value-weighted. All flows have been orthogonalized with respect to returns by taking the residuals from OLS regressions of weekly flows on contemporaneous weekly returns and past 12-week lags of returns. Conjugate flow is the value-weighted flow of all the stocks not in the size segment, value/growth segment or sector of the stock. Conjugate return is defined analogously. BE/ME is book-to-market equity where book equity is for firm's latest fiscal year ending in year $t-1$ and market equity is measured at the end of year $t-1$. ME is market equity measured in June of year t. ROE is U.S. GAAP return on equity for firm's latest fiscal year ending in year $t-1$. The t-statistics, derived from White (1980) standard errors, are in parentheses. * and ** indicate significance at the 5% and 1% levels, respectively.

Independent Variables	Equation (3)	Equation (4)		
Coefficient × Std Dev (in basis pts of return)	1 Week Lag	1 Week Lag	2–4 Week Lag	5–12 Week Lag
Stock return	−30.05**	−31.47**	−14.05**	−11.78**
	(−18.72)	(−19.56)	(−9.90)	(−8.12)
Stock flow	0.15	0.56	−1.67	−4.45**
	(0.13)	(0.46)	(−1.28)	(−3.58)
Size segment return	15.09**	6.46**	8.53**	5.95**
	(14.46)	(5.04)	(6.64)	(5.38)
Size segment flow	1.41	−0.10	3.04*	5.68**
	(1.34)	(−0.09)	(2.55)	(5.08)
Value/growth segment return	7.13**	5.14**	15.22**	8.30**
	(6.29)	(4.52)	(13.06)	(6.69)
Value/growth segment flow	8.22**	9.52**	−3.24**	0.18
	(6.83)	(7.47)	(−2.59)	(0.15)
Sector segment return	4.24**	3.31**	6.37**	−5.74**
	(3.82)	(2.98)	(5.79)	(−5.30)
Sector segment flow	4.32**	2.58*	6.58**	−0.65
	(3.92)	(2.25)	(5.76)	(−0.62)
Conjugate return	−5.51**	−6.40**	11.06**	−10.34**
	(−4.86)	(−5.52)	(8.48)	(−8.50)
Conjugate flow	−6.91**	−6.34**	−6.15**	4.05**
	(−5.45)	(−4.81)	(−4.85)	(3.44)
Stock BE/ME	18.70**	18.04**		
	(12.83)	(12.09)		
Stock log ME	−17.90**	−18.99**		
	(−14.98)	(−15.09)		
Stock ROE	4.92**	4.84**		
	(3.55)	(3.49)		
Adjusted R^2	0.0064	0.0097		

flows may warrant a more meticulous approach toward separating the effects of returns from flows. Thus, we orthogonalize the individual stock and segment flows and returns by estimating OLS regressions on weekly flows with contemporaneous weekly returns and the past 12 weeks of return lags as independent variables. This is done stock by stock and segment by segment for each size, value/growth, sector, and conjugate segment. We take the residuals from these regressions as the orthogonalized flows. In short, we strip away the explanatory power of returns from flows.

Then, we reestimate the equation (3) and (4) regressions with the orthogonalized flow variables in place of the original flow variables. The results, displayed in Table 6, are qualitatively very similar to those in Table 5. We observe that corresponding coefficient estimates and t-statistics on those estimates for the first weekly lag of size, value/growth, sector, and conjugate returns are higher in Table 6 than in Table 5. This is not surprising, given the reduced overlap in explanatory power between returns and flows post orthogonalization. More importantly, we find that even after carefully stripping away the effects of returns, style flows still possess incremental explanatory power over future stock returns. Nearby segment style flows tend to positively forecast stock returns while distant/conjugate segment style flows tend to negatively forecast stock returns. These results lend credence to the base flow results in Table 5 and suggest that they are not the byproduct of some unaccounted for return variation embedded in flows.

B. Anomalous Industries

One criticism leveled at the results is that they may be driven by the anomalous behavior of certain industries during the sample period.[23] For example, during the technology bubble of the late 1990s, many Internet companies had prices that were hard to justify with traditional valuation models (Cooper, Dimitrov, and Rau (2001)). These companies may be responsible for some of the regression results (see Table 5). To allay such concerns, we reestimate the regressions in Table 5 after dropping the industry variables and find that the coefficient estimates are qualitatively unchanged. Past own-style (size and value/growth) flows and returns still reliably and positively forecast stock returns at the weekly horizon.

To further check whether an anomalous industry is affecting the results, we redo the reallocation intensity analysis (see Panel A of Table 2) without technology stocks (which subsume the set of Internet companies).[24] We find that the reallocations across size segments, value/growth segments, and sectors for the nontechnology stock sample also cannot be explained by chance. Over the entire sample period, the t-statistics associated with the reallocation intensities are 18.40, 4.67, and 27.29 for size, value/growth, and sectors, respectively. By removing the technology stocks, the reallocation intensity t-statistic for the sector style spectrum falls from 21.88 to 13.46 in 2001 at the height of the technology bubble. Nonetheless, the sector reallocation intensity t-statistic actually increases between 1995 and 1999, after omitting the technology stocks. It is interesting to note that the omission of technology stocks most affects the reallocation intensity of the value/growth style. This may simply reflect the high returns and extremely low book-to-market values of technology stocks in our sample period.

VI. Conclusion

In classical finance theory, fundamentals affect prices and flows do not. Institutional style investing is therefore uninteresting, as style flows do not affect prices. This paper challenges that view. To analyze style investing, we use high-quality daily flow data from State Street Corporation, covering all the trades of a very large group of institutional investors. We find strong evidence that investors reallocate more intensively across size, value/growth, and industry/sector deciles than across randomly generated deciles. Moreover, style flows have a tangible impact on future stock returns. At weekly frequencies, own-segment style

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[23] We thank the referee for pointing this out.

[24] We define technology firms as firms with the following SIC codes: 3570–3579, 3622, 3660–3692, 3694–3699, 3810–3839, 7370–7379, 7391, and 8730–8734. This gives us a set of 1,649 technology stocks with characteristics information in our sample.

flows and returns positively forecast stock returns, while distant-segment style flows and returns negatively forecast stock returns. These effects pertain to the transitory component of stock returns and fully dissipate after 400–500 weeks. These results are consistent with what we call the weak flow-centric view, which suggests that style flows, at least in part, are related to the temporary component of stock returns. This view is supportive of several behavioral models, particularly that of Barberis and Shleifer (2003).

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