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Journal of Financial Economics 74 (2004) 367–398

JOURNAL OF Financial ECONOMICS

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Style effects in the cross-section of stock returns ☆

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Received 25 April 2002; accepted 29 October 2003

Available online 4 June 2004

Abstract

Using CRSP stock and mutual fund data, we find strong evidence for reversals at the style level (e.g., large value, small growth, etc.). There are significant excess and risk-adjusted returns for stocks in styles characterized by the worst past returns and net inflows. We also find evidence for momentum and positive feedback trading at the style level. These value and momentum effects are driven neither by fundamental risk nor by stock-level reversals and momentum. Taken together, the results are consistent with the style-level positive feedback trading model of Barberis and Shleifer (2003).

JEL classification: G12; G14

Keywords: Style; Style investing; Return predictability

1. Introduction

The propensity to categorize everyday objects is an integral part of human nature. Cars, for example, can be grouped according to their make (Saab or Volvo) or according to their function (SUVs or sports cars). Similarly, stocks can also be

☆We thank Malcolm Baker, John Campbell, Ken Froot, Robin Greenwood, John Heaton, Matt Klaeffling, Paul O'Connell, Bill Schwert, Andrei Shleifer, Jeremy Stein, Tuomo Vuolteenaho, and an anonymous referee for many helpful comments and suggestions.

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0304-405X/$ - see front matter
doi:10.1016/j.jfineco.2003.10.003

grouped into different categories; small versus large stocks, value versus growth stocks, and technology versus non-technology stocks are but just some of the possible dichotomies. One example of categorization at work in Wall Street is style investing, which is, according to Jeremy Siegel, investing such that "money managers rotate between small and large and value and growth stocks," and "is all the rage in Wall Street." (Siegel, 1998, p. 103). Essentially, investors group assets into different asset classes referred to as styles and move money into and out of these styles. This approach to investing appeals to institutional investors as it gives them a convenient framework with which to organize their investment strategies. In response to the demand for style investing, mutual funds have begun to define their investment styles more clearly. See, for example, Bear Stearns Small Cap Value fund and ING Mid Cap Growth fund.

In the first theoretical study of the implications of style investing, Barberis and Shleifer (2003) model an economy with positive-feedback style investors, and fundamental traders. They show that with positive feedback trading at the style level, money chases relative style returns. That is, the higher relative returns of a particular style lead to higher inflows which bid prices away from fundamentals. Subsequently, prices revert to fair value.[1] Their model suggests two interesting and empirically testable predictions. First, the prices of assets within the same style will comove more than their fundamentals, while the prices of assets in different styles will comove less than their fundamentals. Second, style-level momentum and value strategies will be profitable. The profitability of such strategies is not driven solely by their asset-level counterparts.

There is a growing list of empirical studies that are consistent with the predictions of Barberis and Shleifer (2003).[2] On excess comovement, Froot and Dabora (1999) find that prices of seemingly identical stocks traded on different exchanges (e.g., Royal Dutch and Shell) do not move in lockstep, but rather are correlated with the movements of their respective exchanges. Lee et al. (1991) show that discounts of closed-end funds that are listed on the same exchange but hold different securities move together. Barberis et al. (2004) find that when a stock is added to the S&P index, its beta and R^2 with respect to the index increase while its beta and R^2 with respect to stocks outside the index fall.[3] On the profitability of style-level momentum strategies, Moskowitz and Grinblatt (1999) and Asness et al. (1997) successfully apply momentum strategies to industry portfolios and country portfolios, respectively. Lewellen (2002) finds that momentum strategies based on size and book-to-market portfolios are at least as profitable as individual stock momentum. Chen and De Bondt (2004) uncover evidence of style momentum within the S&P 500 index. The evidence for style-level value strategies has been less forthcoming, however. Only Asness et al. (1997) show that a value strategy works well with country portfolios.

[1] We thank the anonymous referee for this parsimonious interpretation.

[2] Other significant contributions to the work on styles include Brown and Goetzmann (1997, 2001) and Chan et al. (2001).

[3] However, the results of these studies are also consistent with a habitat-based model of comovement wherein a group of investors restricts its trading to a specific class of securities and moves in and out of that class together.

This paper goes beyond analyzing the returns from style-level value and momentum strategies. Motivated by Barberis and Shleifer (2003), we seek to distinguish any style effects we find from risk-based, learning, psychological, and positive feedback trading explanations at the stock level, and learning and psychological explanations at the style level. We address the fundamental question: Are style-level value and momentum strategies profitable after controlling for stock-level effects? We focus mainly on the cross-section of stock returns in order to fully distinguish between style-level and stock-level forces.

Instead of focusing on styles based on industries or countries, we focus on the ubiquitous Morningstar style classification system that categorizes funds into small, mid-cap, or large, and growth, blend, or value. We do so for three reasons. First, Morningstar styles coincide with the widespread use of the small/large and value/growth stock dichotomies by practitioners. Second, Morningstar is the leading fund information provider and its style classification is publicly available. Third, many funds name themselves after their Morningstar style analogs, e.g., State Street Research Mid Cap Growth Fund, which suggests that fund clients and managers readily attach the Morningstar fund style to the fund.

According to Barberis and Shleifer (2003), "To test any predictions that emerge from a model of style investing, it is important to have a concrete way of identifying styles. One way of doing this is to look at the products that mutual and pension funds managers offer their clients." Our choice of styles clearly addresses this concern. While it is possible to classify funds based on their loadings on the Fama and French (1993) factors or on stock market indexes like the Russell indexes, these loadings are latent variables and not directly observed by investors. Hence, these investors are less likely to rely on these loadings when determining their style allocation strategies. Moreover, the use of loadings also introduces survivorship bias into the data. To estimate monthly loadings of a fund, one typically needs 30–36 months of return data. This means that one would have to exclude funds that have not existed for more than three years. Consequently, the estimated style returns may be skewed towards those of the better performing funds in the sample.

Our style attributes are culled from mutual fund data because Morningstar styles are defined only for mutual funds (at least prior to 2002), funds often identify themselves explicitly by their styles while stocks do not, and it is much easier to move money in and out of two different styles with mutual funds than with stocks. To move money from style A to style B with mutual funds, one needs only to redeem from one fund in style A and buy into a fund in style B. To replicate the move with stocks, one would have to sell hundreds of stocks in style A and buy hundreds of stocks in style B. The transactions costs of such an endeavor would likely be prohibitive. So, the return of the large value style is the average return of all large value funds. An alternative is to derive style return from the returns to appropriately chosen indexes. The advantage of the current setup is that we can easily compute style flows by aggregating changes in total net assets adjusted for returns, mergers, and acquisitions across all funds in the style. Data on flows into indexes are much less readily available.

We find strong evidence that style-level value strategies based on annual style returns are profitable. Stocks in styles that performed poorly in the past relative to other styles tend to do well in the future. These reversals persist after we control for the usual risk factors. Stocks in the worst performing styles in the past two years subsequently achieve an average abnormal return of 10.6% per year after accounting for the three factors of Fama and French (1997). The use of the three factors as a control for risk can be justified in part by the findings of Liew and Vassalou (2000), who find that SMB and HML contain significant information about future GDP growth. The abnormal return of the worst stocks is 10.1% over and above that achieved by stocks belonging to the best performing styles over the same time period. Evidence for style-level momentum at quarterly horizons is much weaker, however. Stocks in the best performing style in the past quarter attain a three-factor alpha of 6.0% per year, which is 5.3% over and above that attained by stocks in the worst performing style in the past quarter.

Clearly, one interpretation may be that the style reversals and continuations are the result of positive feedback style traders as in Barberis and Shleifer (2003).[4] However, other competing interpretations abound. The style reversals at annual horizons could be due to the preponderance of loser stocks within loser styles that mean-revert as in De Bondt and Thaler (1985). Similarly, the style continuations may be due to a concentration of winner stocks within winner styles whose returns persist as in Jegadeesh and Titman (1993). Other stock-level explanations are plausible, such as: positive feedback trading (De Long et al., 1990), where noise traders buy stocks when stock prices are rising and sell stocks when stock prices are falling; psychological biases (Barberis et al., 1998; Daniel et al., 2001), where investors overreact or underreact to firm cash flow news; and learning (Veronesi, 1999; Lewellen and Shanken, 2002), where investors learn about the distribution of stock returns through successive realizations of firm cash flows. Further, the style effects could be the work of style-level learning or psychological biases.

We distinguish from these competing explanations using a three-pronged approach. First, we adopt a cross-sectional empirical setup and directly control for the profitability of stock-level value and momentum strategies. The inclusion of both long horizon and short horizon stock return lags, and stock ratios as covariates in the regressions allows us to distinguish from the other stock-level explanations. This is because the drivers of the stock-level stories are stock returns and cash flow. To the extent that variation in cash flow is captured by variation in stock returns and stock ratios (e.g., book-to-market equity and dividend yield), our empirical setup allows us to distinguish from these models simultaneously. After implementing these extensive controls, we find that the style-level reversals persist, which suggests that stock-level stories cannot explain the style-level reversals we observe.

[4] Positive-feedback style traders are investors who chase styles that have performed well relative to the rest. This is, in a sense, a combination of a categorization heuristic with trend-chasing behavior. The distinction between positive feedback at the style level and at the stock level is that the former is driven by style returns whereas the latter is driven by stock returns. For example, a positive-feedback style trader may purchase a stock simply because it belongs to a well-performing style even though its own past returns have not been spectacular.

Second, by comparing the strengths of the style continuations and reversals for two sets of styles (value and growth styles versus small and large styles), we find that the continuations and reversals are stronger for those styles that investors perceive to be better substitutes. This agrees with the prediction by Barberis and Shleifer (2003) that the effects of style investing should be more pronounced for styles that are better substitutes, i.e., compete more for inflows. Our findings are hard to reconcile with any learning or psychological story at the style level. For example, it is difficult to understand why investors would overreact more to returns of styles that are better substitutes. It is also hard to rationalize why learning takes place more slowly for styles that are better substitutes.

Third, we find that consistent with the positive feedback style trading view, style flows chase good style returns. This is true even after controlling for stock-level positive feedback trading. Further, style flows share explanatory power with style returns over the space of stock returns. These findings on style flows suggest that style returns affect stock returns through the positive feedback activities of style switchers.

This paper shares some similarities with Kumar (2002) who also examines the relation between style-based investing and stock returns. Kumar (2002) uses high frequency holdings data to examine the interaction of style switching and relative style returns. Like us, he finds style continuations are stronger for the value/growth pair than the small/large pair. However, this paper differs from Kumar (2002) in at least two key respects. First, our sample period of 1984 to 1999 is longer than Kumar's sample period of 1991 to 1996, which allows us to test for style-level reversals. Second, we actively distinguish from the stock-level explanations of cross-sectional predictability. This has been critical in advancing Barberis and Shleifer's (2003) style investing story. This paper is also complementary to that of Asness et al. (2000), who find that value commands a greater premium over growth when the value spread is high. Our style reversal results suggest that the value premium is strongest when value posts poor returns relative to growth in the past few years. However, our results are likely to be distinct from Asness et al. (2000), since we control for the *HML* factor (and thus the value spread) in our sorts.

The remainder of this paper is organized as follows. Section 2 describes the data. Section 3 documents the evidence for style return reversals and persistence. Section 4 adopts a three-pronged approach to explaining style return reversals and persistence. Robustness checks using alternative and complementary methodologies are the focus of Section 5. Section 6 concludes and suggests avenues for further research.

2. Data

The stock data are from the Center for Research in Security Prices (CRSP). Our analysis covers all stocks traded on the NYSE, AMEX, and NASDAQ that are ordinary common shares (CRSP sharecodes 10 and 11), excluding ADRs, SBIs, certificates, units, REITs, closed-end funds, companies incorporated outside the U.S., and Americus Trust Components.

Following Fama and French (1993), we use NYSE breakpoints to determine the breakpoints for small/mid-cap/large stocks as well as growth/blend/value stocks. To minimize data mining concerns, we use the same classification that Fama and French use to construct their *HML* factor. We label stocks below the 30th book-to-market equity (BE/ME) percentile as growth stocks, stocks above the 70th BE/ME percentile as value stocks, and stocks between the 30th and 70th BE/ME percentile as blends. Similarly, we label stocks below the 30th ME percentile as small stocks, stocks above the 70th ME percentile as large stocks, and stocks between the 30th and 70th ME percentile as mid-cap stocks. To avoid ambiguity, we only look at stocks that are the most representative of their style. Thus, we focus on growth stocks below the 20th BE/ME percentile, blends between the 40th and 60th BE/ME percentile, and value stocks above the 80th BE/ME percentile. Similarly, we focus on small stocks below the 20th ME percentile, mid-cap stocks between the 40th and 60th ME percentile, and large stocks above the 80th ME percentile. Nonetheless, our basic results also hold when we include all stocks in our sample.

Several authors have highlighted problems that models commonly have with regard to the treatment of small stocks. Amongst them, Fama (1998) acknowledges that all common asset pricing models including the Fama and French (1993) three-factor model have difficulty explaining the average returns of small stocks. Accordingly, we omit from our analysis penny stocks with prices below \$1 and stocks below the 10th ME percentile. We exclude stocks below the 10th ME percentile for two additional reasons. First, there are few micro-cap funds—small-cap funds holding the smallest stocks—in our mutual fund sample. Second, the median market cap of the micro-cap funds in 2001 is just slightly above the 10th ME percentile for 2001, which suggests that stocks with a ME below the 10th ME percentile are not commonly held by small-cap funds.

We use CRSP mutual fund return and flow data to proxy for style returns and flows, respectively. Mutual fund data are used because the Morningstar equity styles are defined only for funds (at least for the pre-2002 period). Moreover, the association between a fund and its style is often clearer than the association between a stock and its style: fund names often reflect the style of the stocks that they invest, e.g., the Kemper Small Cap Value Fund and the BlackRock Large Cap Growth Equity Fund. Thus, with the advent of the Morningstar style box and the informative nature of mutual fund names, practitioners of style investing have a convenient tool with which to move their funds across styles: mutual funds. We obtain our mutual fund return and flow data from CRSP rather than Morningstar, as it is well known that the latter suffers from survivorship bias. Morningstar data only include surviving funds, causing overall performance measures to be inflated between 40 basis points and 1% per year, depending on the sample period, as shown by Elton et al. (1996). Other researchers who use CRSP mutual fund data include Carhart (1997), Zheng (1999), and Wermers (2000).[5]

[5] According to Elton et al. (2001), returns in the CRSP database for months with multiple distributions on the same day are overstated. This problem has been corrected by CRSP.

Following the standard practice in the mutual fund literature, we omit international funds, sector funds, and domestic hybrid funds. Also, there are concerns that for such funds the Fama-French factors may not adequately cover the associated risks. Since CRSP mutual fund data do not include Morningstar equity style information, we manually transfer historical Morningstar style data from both the Morningstar Principia Pro Plus CD (Feb 2001) and the Morningstar Mutual Fund manuals (1993–1999) onto the CRSP database. As Morningstar style information is not available prior to 1993, we assume that funds that existed prior to 1993 operated under their 1993 style in the years before 1993. According to Warther (1995), "mutual funds played a much smaller role in the pre-1984 markets." Hence, our aim is to verify whether stock data beginning January 1984 can be explained with mutual fund style data. We use mutual fund data beginning January 1978 so as to accommodate a six-year lag.

Note that not all mutual funds in the CRSP database are featured in the Morningstar databases from 1993 to 1999 and style information is not available for funds that terminated before 1993. Of the 32,151 fund-years that we have in our database, we do not have style information on 5,229 fund-years, or, approximately 16% of the fund-years. One way to deal with this is to throw out these fund-years. But that would introduce a survivorship bias into the mutual fund data since many of these fund-years belong to non-surviving pre-1993 funds. Instead, we construct an algorithm based on the informativeness of the fund names, the Wiesenberger fund type code, the ICDI fund objective code, and the Strategic Insight fund objective code reported in the CRSP mutual fund database to estimate the funds' styles. Details of the algorithm are available in the Appendix. Basically, the algorithm takes advantage of simple facts. For instance, funds classified by Strategic Insight as income growth funds (which are often heavily invested in large, dividend-paying stocks) are usually large value funds, and a fund named Munder Mid-Cap Growth Fund would most likely be a mid-cap growth fund. The algorithm identifies the correct style 48% of the time for the post-1992 sample of funds for which we have Morningstar style information. This sample of funds includes funds in the nine styles that we focus on and domestic hybrid funds. Considering the fact that a random assignment will identify the correct style 10% of the time, the algorithm identifies styles well in the post-1992 sample.

We use total net inflows into mutual funds within a style and equally weighted returns of mutual funds within a style to proxy for style flows and style returns, respectively. Style flow is the sum of the net inflows into all the funds in a particular style over a particular time period. Fund net inflows are calculated as the growth in total net assets (*TNA*) adjusted for returns, mergers, and splits. Hence, if fund i did not merge or split in period t, then fund flow in period t is simply

$$Fund\_flow_{i,t} = TNA_{i,t} - (1 + R_{i,t}) * TNA_{i,t-1}, \tag{1}$$

where $TNA_{i,t}$ is the fund's total net assets at the end of period t and $R_{i,t}$ is the return of the fund during period t. If fund B merges into fund A in period t, then the flow of fund A is adjusted downwards by the return-adjusted *TNA* of fund B in period t. If fund A splits into fund B and a smaller fund A at time t, the incremental fund flow is assumed to accrue to fund A in period t. Also, style flow is normalized by the total market capitalization of the style. This, in turn, is derived from stock data using the NYSE *ME* breakpoints listed above. Style return is the mean equally weighted return of all the funds in a particular style. Note that an alternative to using equally weighted style returns is to use *TNA*-weighted style returns. However, the small-cap style return would then be skewed towards the returns of the high-*TNA* small-cap funds. These funds may find it difficult to move funds into or out of the typical small stock owing to their size and thus, may opt to hold more mid-cap or large stocks. Consistent with this reasoning, we find that the spread between the small-cap fund decile portfolios with the highest and the lowest *TNA* loads negatively and significantly on the *SMB* factor. Therefore, high-*TNA* small-cap funds are unlikely to be representative of small-cap funds and we would not be accurately measuring the small-cap style return with the *TNA*-weighted metric.

3. Documenting reversals and persistence in style returns

The first order of business is to establish reversals and persistence in style returns. At the most basic level, the positive feedback style switchers in the Barberis and Shleifer (2003) model should induce reversals (in the long term) and continuations (in the near term) in style returns. We focus on testing for style return reversals given the low frequency of our style data (which comprise annual and quarterly data).

The methodology we follow aims to control for the sources of risk that arise given their covariation with the common risk factors. Basically, a sorting procedure is used to form portfolios of stocks based on past style returns. The returns of portfolios are then regressed on the common factors to verify whether the cross-sectional variation in portfolio returns is explained by the covariation of the returns with the common factors. If after sorting stocks on style return we obtain a return spread that is fully explained by its covariation with the common factors, then it will not bode well for Barberis and Shleifer's (2003) assertion that variation in style prices is driven by noise trading at the style level rather than fundamental risk. Also, by performing such a sorting procedure, we hope to estimate the profits associated with style value strategies.

As a start, we form portfolios of stocks based on their style returns in the past two years. Note that we also form portfolios of stocks based on their style returns in the past three years and past four years. As the results with these sorts are very similar to those discussed in this section, we omit them for brevity. We then estimate the performance of the resulting portfolios. On January 1 of each year, we form nine equally-weighted portfolios of stocks (since there are nine styles), using style returns from mutual fund data. We hold the portfolios for one year, then reform them. This yields a time series of monthly returns on each portfolio from January 1984 to December 1999. Stocks that disappear during the course of the year are included in the equally-weighted average until they disappear, then the portfolio weights are readjusted appropriately. That is, the portfolio weights are rebalanced to equal at the end of every month.

To verify whether any style effects are due to covariation with risk factors, we employ two models of performance measurement: the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. The four-factor model adds to the three-factor model a momentum factor that captures Jegadeesh and Titman's (1993) one-year momentum anomaly. According to Carhart (1997), the four-factor model "eliminates almost all of the patterns in (three-factor model) pricing errors, indicating that it well describes the cross-sectional variation in average stock returns."

We estimate performance relative to the three-factor and four-factor models, respectively, by

$$r_{im} = \alpha_{iM} + \beta_{iM} RMRF_m + s_{iM} SMB_m + h_{iM} HML_m + e_{im} \tag{2}$$

and

$$r_{im} = \alpha_{iM} + \beta_{iM} RMRF_m + s_{iM} SMB_m + h_{iM} HML_m + p_{iM} PR1YR_m + e_{im}, \tag{3}$$

where $m=1,2,\ldots,M$, r_{im} is the monthly return on a portfolio in excess of the one-month T-bill return, $RMRF$ is the excess return on a value-weighted aggregate market proxy, and SMB, HML, and $PR1YR$ are returns on value-weighted, zero-investment, factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns.[6]

The portfolios of stocks sorted on their styles' returns in the past two years demonstrate substantial variation in mean excess returns as shown in Table 1. The portfolio with the worst past returns generates an excess return of 187 basis points per month (22.4%/year), while the spread between it and the portfolio with the best past returns generates an excess return of 105 basis points per month (12.6%/year). During the sample period, the average excess return of the value-weighted market index (RMRF) is 93 basis points per month (11.2%/year). Thus, an investor who buys into styles with the worst returns in the past two years can expect to earn a return of 11.2%/year over and above the value-weighted market index, which is economically significant by any standard.

The three-factor model explains some of the variation of returns induced by the sort on past style returns. The HML factor loading on the spread between portfolios 1 and 9 suggests that the portfolio with the worst past returns contains more value stocks relative to the portfolio with the best past returns. Remarkably, however, after adjusting for size and book-to-market equity, the abnormal return of the investor who buys the portfolio with the worst past returns and shorts the portfolio with the best past returns is still an impressive 84 basis points per month (10.1%/year). The abnormal return for the portfolio with the worst past return is also comparable at 88 basis points per month (10.6%/year).

When measured against the four-factor model, the spread between the worst and the best return portfolio remains roughly unchanged at 82 basis points per month

[6] We thank Mark Carhart for generously providing data on $PR1YR$. See Carhart (1997) for a detailed description of $PR1YR$'s construction.

Table 1
Portfolios of stocks formed on style return in the past two years
Stocks are sorted on January 1 each year from January 1984 to December 1999 into nine style portfolios based on the return of their styles in the last two calendar years. The portfolios are rebalanced monthly so the weights are re-adjusted to equal whenever a stock disappears. Stocks in the style with the lowest past two-year return comprise portfolio 1 and stocks in the style with the highest past two-year return comprise portfolio 9. The variables *RMRF*, *SMB*, and *HML* are Fama and French's (1993) market proxy and factor-mimicking portfolios for size and book-to-market equity. *PR1YR* is Carhart's (1997) factor-mimicking portfolio for one-year return momentum; and alpha is the intercept of the model. The *t*-statistics, derived using White (1980) standard errors, are in parentheses. The number of observations for each regression is 192.

Portfolio	Monthly excess return (%)	Std Dev (%)	Fama-French three-factor model					Carhart four-factor model					
			Alpha	*RMRF*	*SMB*	*HML*	*R-sq*	*Alpha*	*RMRF*	*SMB*	*HML*	*PR1YR*	*R-sq*
1 (Worst returns)	1.87	5.61	0.88**	1.17	0.62	0.41	0.810	1.06**	1.17	0.55	0.37	−0.17	0.819
			(4.55)	(15.97)	(6.04)	(4.14)		(5.25)	(17.49)	(5.56)	(3.99)	(−2.41)	
2	1.36	6.43	0.41*	1.23	0.92	0.20	0.848	0.55**	1.23	0.86	0.17	−0.13	0.853
			(2.10)	(23.21)	(11.13)	(1.65)		(2.92)	(23.37)	(8.97)	(1.44)	(−2.24)	
3	1.23	4.95	0.35*	1.03	0.47	0.35	0.783	0.50**	1.03	0.40	0.31	−0.14	0.792
			(2.11)	(24.27)	(5.48)	(3.74)		(2.91)	(22.23)	(4.43)	(3.41)	(−2.26)	
4	1.02	5.40	0.14	1.08	0.75	0.49	0.786	0.32	1.08	0.68	0.45	−0.17	0.800
			(0.70)	(20.81)	(6.38)	(3.80)		(1.35)	(20.55)	(6.55)	(3.65)	(−1.91)	
5	1.33	5.47	0.40*	1.09	0.47	0.14	0.794	0.53*	1.09	0.41	0.11	−0.12	0.799
			(2.03)	(14.43)	(4.42)	(1.18)		(2.30)	(15.49)	(3.95)	(0.95)	(−1.52)	
6	0.79	5.35	−0.11	1.05	0.41	0.23	0.713	−0.04	1.05	0.38	0.21	−0.07	0.715
			(−0.46)	(11.35)	(3.66)	(1.78)		(−0.14)	(11.08)	(3.37)	(1.71)	(−0.88)	
7	0.82	5.02	−0.16	1.09	0.38	0.59	0.738	0.07	1.08	0.29	0.53	−0.21	0.757
			(−0.74)	(14.44)	(3.78)	(5.11)		(0.30)	(16.18)	(2.79)	(4.82)	(−2.89)	
8	0.73	5.35	−0.15	1.05	0.56	0.36	0.724	−0.13	1.05	0.55	0.36	−0.02	0.724
			(−0.68)	(16.97)	(4.68)	(2.77)		(−0.55)	(17.02)	(4.28)	(2.80)	(−0.21)	
9 (Best returns)	0.81	6.11	0.04	1.05	0.82	−0.13	0.819	0.25	1.04	0.73	−0.18	−0.19	0.829
			(0.21)	(20.03)	(8.94)	(−1.20)		(1.37)	(19.25)	(7.52)	(−1.83)	(−3.06)	
1–9 spread	1.05	3.89	0.84**	0.13	−0.20	0.54	0.150	0.82**	0.13	−0.19	0.55	0.02	0.150
			(3.17)	(1.34)	(−1.41)	(3.82)		(2.91)	(1.32)	(−1.32)	(3.92)	(0.27)	

*Alpha significant at the 5% level.
**Alpha significant at the 1% level.

(9.8%/year) while the abnormal return of the worst return portfolio rises to 106 basis points per month (12.7%/year). The four-factor model does not provide incremental power over the three-factor model in explaining the spread, as both the worst return and best return portfolios load almost equally on the *PR1YR* factor. Also, since the worst return portfolio is negatively correlated with the one-year momentum factor and the mean return of the *PR1YR* factor portfolio is positive (115 basis points per month) during this period, the worst return portfolio's four-factor alpha is even higher than its own three-factor alpha.

Note that while the alphas for the spread and the portfolio with the lowest past style returns are both positively significant with respect to all three models, the alphas for the portfolio with the highest past style returns are not. This may suggest that style investors are more apt to move money away from a style that registered persistent poor performance relative to the other styles than to move money into a style that registered persistent good performance relative to the other styles.

Despite this, there is a clear downward trend in performance or alpha as we move from portfolios 1 to 9. Spearman non-parametric tests, which evaluate the null hypothesis that the return rank and the performance of the portfolios are independent, corroborate this observation. The Spearman tests reject the null hypothesis that the rank of the portfolio and its excess return are independent at the 1% level. The Spearman tests also reject the null hypothesis that the portfolio rank and its alpha are independent at the 1% level for the three-factor model and the four-factor model.

To check that the spectacular returns driven by the technology bubble in 1999 are not responsible for our results, we perform the sort without the 1999 months. We also perform the sort without the January months due to concerns that the January effect may be clouding the results and to address concerns about transaction and implementation lags. Note that we have implicitly assumed that style returns and flows are available to investors immediately. This assumption is not very drastic given we analyze mutual fund flows (mutual funds, unlike hedge funds, do not have significant redemption lags or lockup periods), and we test strategies that are reformed only annually (rebalancing to account for funds that drop out of the database does not affect the portfolio much relative to reforming). In practice, if one has to mail a check to buy fund shares, then the lag might be about one week between the day of one's decision to buy shares and the day of actual share purchase. However, if one electronically transfers money to buy fund shares, then this lag is reduced to 1–3 days. Redemption lags are between 0–2 days. In response to concerns that window dressing by fund managers may be affecting the results (see, e.g., Lakonishok et al., 1991), we redo the sorts without the June and December months. We find that the results are again similar and significant. Also, all our results hold when we value-weight the portfolios. As additional robustness checks, we compute bootstrap standard errors, jackknife standard errors, and Newey and West (1987) standard errors in place of the White (1980) standard errors for the coefficients. Our results are robust to these adjustments.

Fig. 1 complements the results in Table 1. It illustrates the monthly cumulative average residuals (CARs) of portfolios sorted on past two-year style returns, where

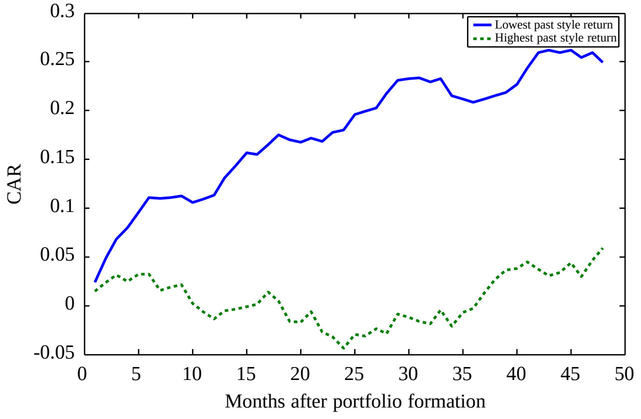

Fig. 1. Cumulative average residuals for portfolios of stocks sorted on their style returns in the past two-years (1–48 months into the test period). Cumulative average residual (CAR) is the difference between a portfolio's excess return and *RMRF* (the excess return on a value-weighted aggregate market proxy). Each January between 1984 to 1999, portfolios of stocks are formed based on a two-year formation period. The monthly excess returns of these portfolios are recorded over a four-year window (if possible). The differences between the excess returns and *RMRF* are then averaged to calculate the CARs.

CAR is defined as the excess return of the portfolio minus *RMRF*. Hence, the difference between the CAR of the loser style portfolio and the CAR of the winner style portfolio at the 12th month corresponds to 12 times the excess return spread in Table 1. The outstanding features of Fig. 1 are undoubtedly the asymmetry between the performance of the loser portfolio and that of the winner portfolio, and the persistent overperformance of the loser portfolio over the holding period of four years. Again, this brings us back to the point that investors may be more responsive to poor style performance than good style performance. This is reminiscent of the asymmetry in performance of loser stocks and winner stocks based on long-horizon stock return lags in De Bondt and Thaler (1985). This does not in itself suggest that investors overreact at the style level. De Bondt and Thaler (1985) document stock return reversals. The reason stock returns mean-revert is still an open question. Both positive feedback models and learning models can explain the stock reversals. We will show later that it is unlikely that either overreaction or learning at the style level drives our results. We will revisit this issue when we investigate the behavior of style flows in Section 4.3.

So far, we have found strong evidence of style-level reversals at annual horizons. When we test for style-level continuations, we find that style return momentum is weak, at least at the quarterly horizon. An analogous sort on quarterly style returns one quarter ago yields a significantly positive three-factor alpha of 50 basis points per month (6.0%/year) for the portfolio with the highest past quarterly style return, and a insignificantly positive three-factor alpha spread of 44 basis points per month (5.3%/year) between that portfolio and the portfolio with the lowest quarterly style return. One reason for the relatively weak evidence for style momentum may be that style continuations occur at shorter horizons (e.g., daily or weekly horizons). At the quarterly horizon, the short term style-level momentum may have lost steam and started to give way to style-level reversals. Nonetheless, the lack of strong evidence for style-level momentum at quarterly horizons requires that we adopt a cautious approach and obtain more evidence before linking the style effects to a Barberis and Shleifer (2003) story.

Overall, our results suggest that first, there is a strong overperformance of stocks in styles that have the worst past annual returns. Second, there is a significant spread between returns of stocks in styles with the worst past returns and those in styles with the best past returns. Third, these findings cannot be easily explained by risk factor covariation in the sense of Fama and French (1993).

4. Explaining reversals and persistence in style returns

In the previous section, we document strong evidence for style return reversals at annual horizons and weaker evidence for style return continuations at quarterly horizons. In this section, we adopt a three-pronged approach to narrow down the plausible explanations for the behavior of style returns. First, we test whether stock-level explanations can account for the style-level reversals and continuations. Second, we examine the variation in strengths of the style effects across different sets of styles. Third, we check for positive feedback trading at the style level and gauge the explanatory power of style flows on stock returns.

If the style-based positive feedback trading story of Barberis and Shleifer (2003) holds, then the style effects should persist after controlling for stock reversals and continuations. Moreover, the style effects should be stronger for pairs of styles with smaller (i.e., more negative) flow correlations. Further, positive feedback trading at the style level should exist over and above stock-level positive feedback trading. Finally, style flows should share explanatory power with style returns over the space of stock returns.

4.1. Distinguishing from stock-level explanations

In this section, we investigate whether the long-term reversals and mid-term continuations at the style level are distinct from the long-term reversals (De Bondt and Thaler, 1985) and mid-term continuations (Jegadeesh and Titman, 1993) already documented at the stock level. One potential explanation for the style reversals we observe is that there is a preponderance of loser stocks within the loser styles; when the returns of these stocks mean-revert, so too do the returns of their style. Similarly, a plausible explanation for the style continuations we observe is that there is a preponderance of winner stocks within these winner styles. If, as in Barberis and Shleifer (2003), the style effects are driven by the interaction of rational arbitrageurs and style switchers, then the style reversals and continuations should persist after controlling for stock reversals and continuations.

Also, we test whether the style effects are distinct from other stock-level explanations. In particular, we test whether style effects are different from three important classes of models which explain stock-level predictability: learning models (Veronesi, 1999; Lewellen and Shanken, 2002), psychological models (Barberis et al., 1998; Daniel et al., 2001), and positive feedback trading models (De Long et al., 1990). The central theme underlying these models is that variation in stock returns is driven by investor reaction to past stock returns and/or stock ratios.

Finally, we determine how much of the variation in style returns is driven by variation in fundamental risk as captured by stock characteristics (Fama and French, 1992; Barberis and Shleifer, 2003) provides a story of noise trading at the style level. If their predictions hold, it must be that variation in style prices cannot be due solely to variation in risk.[7]

We perform the above tests by estimating Fama and MacBeth (1973) regressions on monthly stock returns with annual style returns and quarterly style returns as the independent variables. The cross-sectional setup allows us to distinguish most directly from among competing hypotheses by letting us control simultaneously for risk proxies, stock ratios, long-horizon stock return lags, and short-horizon stock return lags. In addition, the cross-sectional setup allows us to focus on both relative style attributes and stock returns, in the spirit of Barberis and Shleifer (2003). By regressing stock returns on style returns in a cross-sectional framework, we can determine how a one unit increase in a style's returns, keeping all other styles' returns constant, affects the returns on the stocks in that style, keeping the returns of the other stocks in the other styles constant.

We consider style attributes such as lagged style returns (up to five years) and lagged quarterly style returns (up to four quarters). For each style attribute, we test it against the following model of stock returns:

$$\begin{aligned} r_{im} = {} & a_m + b_m x_{it} + c_m \ln((BE/ME)_{it}) + d_m \ln(ME_{it}) + e_m \beta_{it} \\ & + f_{m1} QPASTRET_{it-1} + f_{m2} QPASTRET_{it-2} + f_{m3} QPASTRET_{it-3} \\ & + f_{m4} QPASTRET_{it-4} + g_m (D/P)_{it} + h_m (DUM\_D/P)_{it} + \varepsilon_{im}, \end{aligned} \tag{4}$$

where $i = 1,...,N$, $t = 1,...,T$, and $m = 1,...,12T$. The variables in Eq. (4) are defined as follows: m is a month in year t; r_{im} is the return on stock i in month m; x_{it} is a style attribute of stock i; BE_{it} is the book value of common equity plus balance-sheet deferred taxes for each firm's latest fiscal year ending in calendar year $t-1$; $(BE/ME)_{it}$ is measured using market equity in year $t-1$; ME_{it} is firm size and is measured in June of year t; β_{it} is the post-ranking beta of the size-beta portfolio that the firm is in at the end of June of year t as in Fama and French (1992); $QPASTRET_{it-j}$ is the

[7] There is some contention as to whether factor loadings or stock characteristics (e.g., size and book-to-market equity) are better measures of risk (Daniel and Titman, 1997; Lewellen, 1999). Consequently, there has been much academic debate on this topic. In the interest of brevity, we do not take a stand as to whether factor loadings or stock characteristics better capture risk. Moreover, defending such a stand will take us too far afield from the topic at hand. Instead, to mitigate uncertainty concerning the possible sources of risk, in this section we further investigate the impact of style attributes on stock returns after taking into account stock characteristics (book-to-market equity and market equity).

quarterly return of the stock j quarters ago; $(D/P)_{it}$ is the dividend yield of the stock lagged one year; $(DUM\_D/P)_{it}$ is the dummy variable that takes a value of one when $(D/P)_{it}$ is zero and a value of zero when $(D/P)_{it}$ is positive. We follow the conventions of Fama and French (1992) when computing the stock characteristics (e.g., size, book-to-market equity, etc.).

Eq. (4) includes the standard risk proxies such as the stock's beta, book-to-market ratio, and market equity that are featured in the basic regression that Fama and French (1992) estimate. In addition to these stock characteristics, Eq. (4) also includes dividend yield and four lags of quarterly stock returns. We incorporate dividend yield in response to the documented predictive ability of the dividend yield on future dividends (Campbell and Shiller, 1988); four lags of quarterly stock returns are included to capture the Jegadeesh and Titman (1993) one-year momentum effect.

For each month from January 1984 to December 1999, we estimate the cross-sectional regression specified by the model. As in Fama and MacBeth (1973), we then average the coefficient estimates across the complete sample period. For example, for each regression, a total of 192 cross-sectional regressions are estimated, which average about 734 observations each for a combined total of 140,946 observations.

For the control variables (the stock characteristics) in the regressions, we obtain coefficient estimates that broadly conform to those in the existing literature. Consistent with Fama and French (1992), the coefficient estimates on beta are insignificantly different from zero, the coefficient estimates on the log of book-to-market are either insignificantly positive or significantly positive, and the coefficient estimates on log of market equity are significantly negative. The coefficient estimates on quarterly stock return lagged two to four quarters are significantly positive, which is in line with Jegadeesh and Titman (1993). Also, the coefficient estimates on dividend yield are insignificantly positive, suggesting that the predictive ability of dividend yield on returns is mild but in the direction posited by Campbell and Shiller (1988).

Table 2 reports the coefficient estimates for the annual style return lags and the quarterly style return lags and clearly suggests that the style-level reversal effects are strong and persist even after controlling for the various stock characteristics, returns, and ratios. All the annual style return lags are negatively significant at the 5% level of confidence. The reversal effects are strong for annual style returns lagged two, three, and four years. For instance, a one percentage-point increase in the return of a style two years ago, relative to that of all the other styles, decreases the returns to the stocks in that style by an average of 11.25 basis points per month (1.35%/year) relative to the stocks in other styles. It is important to put the magnitude of the style return coefficients in perspective. Between 1984 and 1999, the average cross-sectional standard deviation of annual stock returns in our sample is about 64%, while that of style returns is about 9%. Hence, a one-standard deviation decrease in a style's returns two years ago increases the annual returns of the stocks in that style by about 0.2 standard deviations.

The evidence for style-level momentum is much milder, at least at the quarterly horizon. The coefficient estimates for the quarterly style return lags become more positive as we decrease the lag. However, the coefficient estimate on quarterly style

Table 2
Fama-MacBeth (1973) cross-sectional regressions on monthly stock returns (with quarterly and annual style attributes)
Cross-sectional regressions are estimated for each month from January 1984 to December 1999 across all stocks in the sample at that time. The dependent variable is the firm's monthly return. The independent variables are quarterly style returns and annual style return lags, as well as firm attributes such as the firm's beta, log of book-to-market ($\ln(BE/ME)$), log of size ($\ln(ME)$), dividend yield (D/P), and past returns. Annual style return is the equally weighted annualized return over all the funds in the style over the year; beta is the post-ranking beta of the size-beta portfolio the firm is in at the end of June of year t, as in Fama and French (1992); BE is the book value of common equity plus balance-sheet deferred taxes and is for each firm's latest fiscal year ending in calendar year $t-1$; BE/ME is measured using market equity in year $t-1$; and firm size ME is measured in June of year t. Each style attribute is tested individually against two models of stock returns. In Eq. (4), the independent variables are the style return lag, $\ln(BE/ME)$, $\ln(ME)$, firm's past quarterly returns, D/P, and dum_D/P (which equals one when D/P equals zero, and is zero otherwise). In Augmented Eq. (4), the independent variables are those in Eq. (4) and the past 2- to 5-year annual return lags of the firm. The reported estimates are the time-series averages of monthly cross-sectional regression slope estimates as in Fama and MacBeth (1973). For each Eq. (4) regression, a total of 192 cross-sectional regressions are estimated, which average about 734 observations each for a combined sample of about 140,946 observations. The t-statistics, in parentheses, are on the time-series means of the coefficients. The coefficients for the firm attributes are suppressed for brevity.

Independent variables (coefficients $\times$ 100)	Eq. (4) (controlling for risk proxies and stock ratios)	Augmented Eq. (4) (controlling for risk proxies, stock ratios, and long horizon stock returns)
Style return lagged 1 quarter	2.42	2.42
	(1.52)	(1.62)
Style return lagged 2 quarters	0.83	0.00
	(0.47)	(0.02)
Style return lagged 3 quarters	−0.92	−1.33
	(−0.45)	(−0.67)
Style return lagged 4 quarters	−3.58*	−3.33*
	(−1.77)	(−1.87)
Style return lagged 1 year	−7.65**	−4.56*
	(−2.72)	(−1.74)
Style return lagged 2 years	−11.25**	−7.88**
	(−3.64)	(−2.92)
Style return lagged 3 years	−11.06**	−9.77**
	(−3.06)	(−2.93)
Style return lagged 4 years	−12.38**	−10.15**
	(−3.46)	(−3.34)
Style return lagged 5 years	−10.52**	−10.09**
	(−2.05)	(−2.44)
Number of observations	140,946	108,020

*Significant at the 10% level.
**Significant at the 5% level.

return at the first quarterly lag, while positive, insignificantly differs from zero. One interpretation is that style-level continuations occur at frequencies of less than a quarter. Another interpretation is that style-level continuations are mild on average but stronger for certain styles. We shall revisit this issue in the next section.

So far we have found that a style value strategy works well at annual horizons after controlling for risk proxies in the form of stock characteristics. However, it may well be that the value effects we witness at the style level are driven by the well-documented value effects at the stock level (De Bondt and Thaler, 1985). If the low relative returns to style A are due to the preponderance of loser stocks in style A, then style A's price is likely to rebound in the future when the prices of the loser stocks revert to fair values. To verify whether stock-level reversals are driving our results, we estimate Fama-MacBeth regressions on monthly stock returns with past stock returns two to five years ago and with the stock control variables in Eq. (4). The coefficient estimates on the long-horizon stock return lags suggest that stock returns two, three, and five calendar years ago mildly and negatively explain future stock returns (t-statistics $\approx$ 2). Hence, we augment Eq. (4) with the following control variables: past two-year, three-year, four-year, and five-year stock returns.

The results of this new model specification are provided in the right-most column of Table 2. Note that the number of observations is significantly reduced with this new specification as we now require each stock in our sample to have five years of lagged annualized returns. We find that the significance of the coefficient estimates for the lags of style returns easily survives the inclusion of the long horizon stock return lags. This is not surprising. In our sample, 97% of the past-35 extreme loser stocks based on a five-year evaluation period, as in De Bondt and Thaler (1985), have either market capitalizations below the NYSE 10% ME percentile or share prices under $1. Since these extreme loser stocks drive the De Bondt and Thaler overreaction effect, and because we exclude these micro-cap and penny stocks from our analysis, the coefficient estimates in Eq. (4) should not be strongly affected by mean-reversion at the stock level. Overall, this suggests that the profitability of style-level value strategies is not driven solely by De Bondt and Thaler (1985) stock-level reversals. This finding is consistent with the prediction of Barberis and Shleifer (2003) that the profitability of style-level value strategies is not driven by that of asset-level value strategies.

Moreover, since we included both short-horizon and long-horizon stock returns in the controls, the style reversals cannot be driven by positive feedback at the stock level. This allows us to rule out positive-feedback trading models such as De Long et al. (1990) and Hong and Stein (1999). We note that the coefficient estimates on stock returns two, three, and five calendar years ago remain significant (t-statistics $\approx$ 2.2) with the inclusion of the style attributes, which suggests that stock-level reversals are not driven solely by reversals at the style level. Barberis and Shleifer (2003) allude to this possibility when they acknowledge that, "In practice, at least some noise trading is likely to be an asset-level phenomenon."

The use of lagged stock characteristics, returns, and ratios as control variables in the regressions with style returns also allows us to distinguish the style effects from two other important classes of models mentioned earlier in this section. First, to the extent that investors learn about the true value of a stock through its past returns (short horizon and long horizon) and ratios (dividend yield and book-to-market equity), the style effects are not the result of individual learning. This allows us to separate from the learning models proposed by Brennan and Xia (2001), Veronesi (1999), and Lewellen and Shanken (2002). Second, to the extent that investor biases are driven by past realizations of stock returns and ratios, the style effects are not the result of investor psychological biases at the stock level, as advocated in the psychological models of Barberis et al. (1998) and Daniel et al. (2001).

4.2. Variation in style effects across styles

So far, our analyses have focused on nine different styles in a cross-sectional framework. The cross-sectional framework allows us to analyze the effects of a change in a style return relative to, say, the average return across all styles. The cross-sectional framework also allows us to control directly for the stock characteristics that are known to explain the cross-section of stock returns. Such controls are instrumental in distinguishing the style effects from the learning, psychological, and positive feedback trading stories at the individual stock level. The focus on nine different styles also allows us to formulate our inferences based upon the full set of information.

Nonetheless, it may be useful to consider subsets of the styles in our sample. Barberis and Shleifer (2003) posit the existence of twin styles. Twins are styles that investors perceive to be substitutes: When an investor pulls funds from one style due to poor relative performance, she ploughs these funds into its twin style. Twins are therefore natural competitors for style investors' funds. The predictions of Barberis and Shleifer (2003) most strongly apply to the relative returns of twin styles. However, their predictions also hold (but become less sharp) when more than two styles are considered.

Two natural pairs of candidates for twins emerge from the Morningstar style classification system: value and growth, and small and large. The correlation between value and growth raw quarterly flows from the first quarter of 1978 to the second quarter of 2000 is -0.099, while the correlation between small and large raw quarterly flows in that same period is 0.565. Hence, value and growth seems to be a better choice for the set of twin styles. If what drives the returns to a style value (momentum) strategy is fund shifting by style investors, i.e., if Barberis and Shleifer's (2003) predictions hold, then the results for style returns should be sharper when we constrain ourselves to value and growth styles than when we constrain ourselves to small and large styles.

In this section, we investigate whether style reversals and continuations are stronger when we focus on value and growth styles. First, we estimate Eq. (4) regressions in the previous section with only value and growth stocks in the sample (i.e., we exclude stocks that belong to large blend, mid-cap blend, and small blend styles from the subsample). Second, we re-estimate the regressions with only the small and large stocks in the sample (i.e., we exclude stocks that belong to mid-cap growth, mid-cap blend, and mid-cap value styles from the subsample). Then, we

Table 3
Fama-MacBeth (1973) cross-sectional regressions on monthly stock returns (with subsets of styles)
Cross-sectional regressions are estimated for each month from January 1984 to December 1999 across subsets of stocks in the sample. The dependent variable is the firm's monthly return. The independent variables are quarterly style returns and annual style return lags, as well as firm attributes such as the firm's beta, log of book-to-market (ln(BE/ME)), log of size (ln(ME)), dividend yield (D/P), and past returns. Annual style return is the equally weighted annualized return over all the funds in the style over the year; beta is the post-ranking beta of the size-beta portfolio the firm is in at the end of June of year t, as in Fama and French (1992); BE is the book value of common equity plus balance-sheet deferred taxes and is for each firm's latest fiscal year ending in calendar year $t-1$; BE/ME is measured using market equity in year $t-1$; and firm size ME is measured in June of year t. The first series of regressions reported are estimated on stocks in value and growth styles only (small growth, mid-cap growth, large growth, small value, mid-cap value, and large value). The second series of regressions reported are estimated on stocks in small and large styles only (small growth, small blend, small value, large growth, large blend, and large value). The reported estimates are the time-series averages of monthly cross-sectional regression slope estimates as in Fama and MacBeth (1973). The t-statistics, in parentheses, are on the time-series means of the coefficients. The coefficients for the firm attributes are suppressed for brevity.

Independent variables (coefficients × 100)	Value and growth styles	Small and large styles
Style return lagged 1 quarter	5.00*	1.08
	(2.21)	(0.52)
Style return lagged 1 year	−13.65**	−9.76*
	(−3.28)	(−2.19)
Style return lagged 2 years	−14.90**	−13.33*
	(−3.35)	(−2.34)
Style return lagged 3 years	−18.27**	−14.25**
	(−3.43)	(−3.00)
Style return lagged 4 years	−16.22**	−14.59**
	(−3.32)	(−3.69)
Style return lagged 5 years	−15.28*	−7.17
	(−2.04)	(−1.31)

*Significant at the 5% level.
**Significant at the 1% level.

compare the strengths of the style reversal and continuation effects inferred from the two sets of coefficient estimates.

Consistent with our intuition, the coefficient estimates on the style returns displayed in Table 3 suggest that the style reversal and continuation effects are stronger with value and growth styles than with small and large styles. All the coefficient estimates for the value/growth subsample are larger in magnitude than the corresponding coefficient estimates for the small/large cap subsample. Further, larger t-statistics (in magnitude) are reported for the style return coefficient estimates with the value/growth subsample than for those with the small/large cap subsample (except for style returns lagged four years). This is consistent with the Barberis and Shleifer (2003) prediction that style effects should be stronger when considering twin styles.

The above results together suggest that the style value and continuation effects documented are the result of investor responses to shocks to relative style returns. Moreover, investors are not equally responsive to all styles. This second point is important. Learning and psychological stories at the style level all have trouble explaining why the style value/momentum effects are stronger for some style combinations and weaker for others. It is difficult to rationalize why an investor finds it harder to learn the true fundamental value of value and growth styles than to learn the true fundamental value of small and large styles. The style-level positive feedback story of Barberis and Shleifer (2003) explains this phenomenon nicely. It links the magnitudes of the style effects closely to the flow correlation between styles. The more negative the flow correlation between two styles, the more investors regard the styles as substitutes, the more investors respond to the relative returns between the two styles, and the greater the resultant deviation from fair value.

Note that if the style returns for the value and growth set are more volatile than the style returns for the small and large set, then a Bayesian-updating investor should give less weight to the past for the value/growth set, and this in turn may explain some of the greater underreaction in style returns for the value/growth set.[8] Also, this may also support a style-level learning story. However, both the average cross-sectional standard deviation and the average time-series standard deviation of annual style returns for the value/growth subsample are smaller than the corresponding statistics for the small/large cap subsample. It is therefore difficult to argue that Bayesian investors should overreact or underreact at the style level more with the value/growth subsample. It is also difficult to argue that learning at the style level takes place more slowly with this subsample. Note that this does not reverse our previous result from Table 3, namely that the effects of value/growth style returns are stronger than those of small/large style returns. That is, a one-standard deviation increase in value/growth style returns still induces a greater decrease in monthly stock returns (in standard deviation terms) than does a one-standard deviation increase in small/large style returns.

In summary, the results from this section suggest that the style value and momentum effects are stronger for styles that investors perceive to be good substitutes (e.g., value and growth styles) than for styles that investors perceive to be weak substitutes (e.g., small and large styles). Also, the style value/momentum effects are unlikely to be the result of learning or psychological stories at the style level.

4.3. Testing the implications of style investing on style flows

The previous sections have focused on the effects of style returns on stock returns. However, style flows also play an important role in any style investing story. In this section, we test out the implications that a style investing story has on flows. First, we test whether positive feedback trading occurs at the style level. Next, we verify whether style flows explain the cross-section of stock returns and whether any

[8] We thank the referee for pointing this out to us.

explanatory power of style flows on stock returns overlaps with the explanatory power of style returns on stock returns.

Since the style effects proposed by Barberis and Shleifer (2003) are driven by positive feedback trading at the style level, it is important to verify whether style flows chase style returns. However, even if we find that flows chase returns at the style level, this could well be the result of investors chasing well-performing stocks that concentrate within certain well-performing styles. Hence, we must control for positive feedback trading at the stock level to distinguish the style effects from the stock-level positive feedback stories proposed by De Long et al. (1990) and Hong and Stein (1999).

One way of doing so is to sort the universe of nine styles by returns, or, four-factor alpha, and note whether the flows in the current and subsequent quarters are higher for styles with higher returns/alphas. This method affords us the luxury of considering flows to all styles simultaneously and allows us to utilize all the information at hand.

Toward this end, for each quarter, we sort the styles in our universe into nine portfolios based on their returns. We then examine the average flow to these portfolios in the formation quarter, as well as the average flow one quarter after, two quarters after, and one quarter before the formation quarter. We also sort on quarterly four-factor alphas to control for stock-level positive feedback trading. This methodology is in the spirit of Gruber (1996).

The results from Table 4 corroborate the Barberis and Shleifer (2003) style switching story. For the return sort in Panel A, Spearman tests reject the null hypothesis that the return rank and the flow in the formation quarter are independent at the 1% level of significance. The tests also reject the null that the return rank and flow in the subsequent quarter are independent at the 1% level of significance. The results are represented graphically in Fig. 2. A clear downward trend in flows emerges for the t and $t+1$ columns as we move from the high-return portfolio to the low-return portfolio in Fig. 2. This suggests that style flows react to style returns within the quarter.

This flow pattern also exists when we examine portfolios sorted on four-factor style alpha. From the results in Panel B of Table 4, Spearman tests reject the null hypothesis that the alpha rank and the flow in the formation quarter are independent at the 10% level of significance. The tests also reject the null that the alpha rank and flow in the subsequent quarter are independent at the 1% level of significance. Thus, after controlling for stock-level positive feedback trading, we find that style flows chase style returns at quarterly horizons.

In Section 3, the asymmetry in returns between the worst style return portfolio and the best style return portfolio suggests that investors react most strongly to styles with poor relative returns at annual horizons. Yet Fig. 2 suggests that investor reactions to the best and the worst performing styles at quarterly horizons are of comparable magnitude, given the steady downward trend in flow as we move down column t. In fact, if anything, we find that the reaction to the best quarterly style returns is slightly stronger than the reaction to the worst quarterly style returns (consistent with the mutual fund literature). To see this, compare the difference in

Table 4
Flows into portfolios sorted on quarterly style return/alpha
Each quarter, nine portfolios are sorted based on their style return/four-factor alpha. The average flows in the formation quarter t, as well as the flows one quarter before, one quarter after and two quarters after the formation quarter are calculated. Spearman's rho and the p-values that test the hypotheses that the return rank and the flow of the portfolios are independent are listed. The sample period is from the first quarter of 1984 to the last quarter of 1999. In Panel A, the portfolios are sorted on style return. In Panel B, the portfolios are sorted on style four-factor alpha.

Style return rank (t)	Flow ($t-1$)	Flow (t)	Flow ($t+1$)	Flow ($t+2$)
Panel A: sorted on style return (t)				
1	2.87	7.11	7.04	5.15
2	2.96	4.97	4.59	3.91
3	2.30	3.44	4.23	4.34
4	3.10	5.34	4.69	2.38
5	4.13	1.96	3.45	4.55
6	4.30	4.06	2.98	3.40
7	6.36	2.89	3.97	3.42
8	3.92	2.26	−0.05	2.06
9	3.53	1.43	2.55	4.25
Spearman's rho	0.68	−0.80	−0.88	−0.48
p-value	0.04	0.01	0.00	0.19
Panel B: sorted on style four-factor alpha (t)				
1	4.16	5.63	6.16	6.55
2	4.51	5.86	5.27	4.21
3	3.87	4.93	2.36	3.78
4	3.66	4.14	3.58	3.70
5	1.57	1.65	3.92	3.24
6	4.47	3.70	3.23	3.08
7	2.73	2.29	2.52	3.07
8	3.51	1.26	1.24	2.95
9	4.97	3.99	5.18	2.86
Spearman's rho	−0.42	−0.60	−0.83	−0.42
p-value	0.26	0.09	0.01	0.26

flows into portfolios 1 (best return portfolio) and 2 to the difference in flows into portfolios 8 and 9 (worst return portfolio), from the flow(t) column in Table 4. One reason for this dissonance is that in our sample, the styles with the worst annual style returns are usually the styles with the worst quarterly returns, while the converse is not true. We find that this occurs in the later half of our sample, and thus explains the apparent asymmetry in Section 3.

In addition to chasing style returns, if the Barberis and Shleifer (2003) story holds true, style flows should explain the cross-section of stock returns. Further, the explanatory power of style flows on stock returns should overlap with that of style

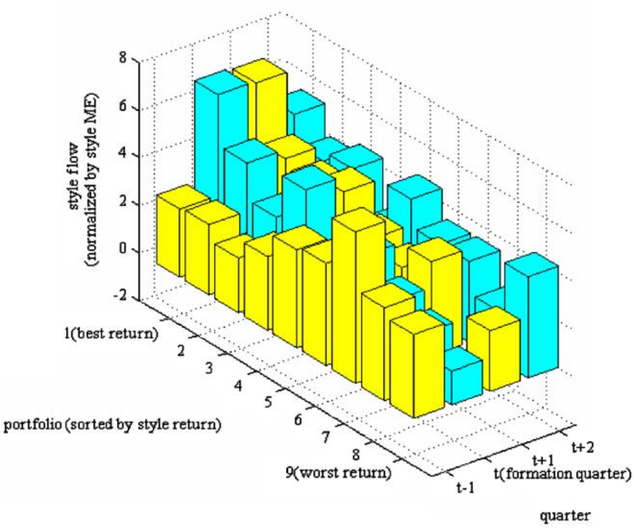

Fig. 2. Total net cash inflows into styles sorted on their mean equally weighted return in quarter t. The sample period is from the 1st quarter of 1984 to the 4th quarter of 1999. To generate the quarter-t series, each quarter, styles are sorted into nine portfolios based on their style return in the concurrent quarter. Style return is the mean equally weighted return of funds in that style. The style flows of these portfolios are then averaged across the sample period. To generate the quarter-$t+1$ series, each quarter, styles are sorted into nine portfolios based on their style return in the preceeding quarter. The style flows of these portfolios are then averaged across the sample period. The quarter-$t+2$ and quarter-$t-1$ series are generate analogously. The variable ME is market equity.

returns. This is because in their model, it is the style switching activities of positive feedback investors that drive the continuations and reversals in style prices.

The main result from Section 3.1 is that annual style returns strongly explain stock returns in the future. Hence, when we include both annual style flows and annual style returns in Eq. (4) cross-sectional regression of Section 3.1, the explanatory power of style returns should fall relative to the case in which style returns are the only style attributes among the regressors. The results of such regressions displayed in the left-most column of Table 5 confirm this hypothesis. The estimated coefficients on style return lags in Table 5 are all smaller in magnitude and less significant than the corresponding Eq. (4) coefficients in Table 2. Moreover, just as low relative style returns explain high relative stock returns, low relative style flows should also explain high relative stock returns, as suggested by a positive feedback style investing story. The right-most column of Table 5 reports the coefficient estimates on style flow when stock returns are regressed on annual style flow lags and other stock controls. All five point estimates for the coefficients on the style flow lags are negative while three are significant at the 5% level of significance.

The flow results from this section point to a positive feedback style investing story. Our finding that positive feedback occurs at the style level may not be surprising given the results of Froot et al. (2001), who find that portfolio flows chase portfolio

Table 5
Fama-MacBeth (1973) cross-sectional regressions on monthly stock returns (controlling for style flows)
Cross-sectional regressions are estimated for each month from January 1984 to December 1999 across all stocks in the sample at that time. The dependent variable is the firm's monthly return. The independent variables are annual style flow and annual style return lags, as well as firm attributes such as the firm's beta, log of book to market ($\ln(BE/ME)$), log of size ($\ln(ME)$), dividend yield (D/P), and past returns. Annual style return is the equally weighted annualized return over all the funds in the style over the year; beta is the post-ranking beta of the size-beta portfolio the firm is in at the end of June of year t, as in Fama and French (1992); BE is the book value of common equity plus balance-sheet deferred taxes and is for each firm's latest fiscal year ending in calendar year $t-1$; BE/ME is measured using market equity in year $t-1$; and firm size ME is measured in June of year t. Two sets of regressions are run. For both sets, the independent variables include $\ln(BE/ME)$, $\ln(ME)$, firm's past quarterly returns, D/P, and dum_D/P (which equals one when D/P equals zero, and is zero otherwise). For the first set, the style return lag and the style flow lag (which is contemporaneous with the style return lag) are also included, while the second set only includes the style flow lag. The reported estimates are the time-series averages of monthly cross-sectional regression slope estimates as in Fama and MacBeth (1973). The t-statistics, in parentheses, are on the time-series means of the coefficients. The coefficients for the firm attributes are suppressed for brevity.

Independent variables (coefficients $\times$ 100)	Style return (controlling for style flow)	Style flow
Lagged 1 year	-6.76^{**}	-17.28^{**}
	(-2.10)	(-2.73)
Lagged 2 years	-8.22^{**}	-20.86^{**}
	(-2.44)	(-3.07)
Lagged 3 years	-9.45^{**}	-22.66^{**}
	(-2.47)	(-2.69)
Lagged 4 years	-9.65^{**}	-15.65^{*}
	(-2.55)	(-1.94)
Lagged 5 years	-9.24^{*}	-13.21
	(-1.80)	(-1.61)

* Significant at the 10% level.
** Significant at the 5% level.

returns. What is probably more intriguing is that style flows follow style returns even after controlling for stock-level positive feedback trading. This is suggestive of positive feedback trading forces at the style level that are not just the sum total of positive feedback forces at the stock level. Moreover, the fact that style flows and style returns share explanatory power over the space of stock returns is suggestive of the style return to style flow to stock return linkage unique to a positive feedback style investing story.

5. Robustness tests

The results of Section 4 have advanced the style investing interpretation for the style reversal and continuation effects we document using a tri-faceted approach.

First, the style effects are found to be distinct from stock-level explanations, including stock-level momentum and reversals. Second, the variation in the style reversals and continuations, among different sets of styles, bears a one-to-one correspondence with flow correlations and is consistent with a style investing story. Third, the behavior of style flows vis-à-vis style returns and the shared explanatory power of style flows and style returns are supportive of a Barberis and Shleifer (2003) interpretation.

In this section, we augment those results with a series of robustness tests using complementary techniques. First, we report two-pass portfolio sorts on style returns and stock returns to further isolate the effects of style returns on the cross-section of stock returns. This complements the cross-sectional regressions, which control for stock returns, that are reported in Section 4.1. Next, we perform time-series tests on persistence in value/growth relative returns to further test style continuations at quarterly horizons. This complements the cross-sectional regressions with quarterly style returns that are reported in Sections 4.1 and 4.2.

5.1. *Two-pass sorts on style returns and stock returns*

The cross-sectional results in Table 2 suggest that the explanatory power of past style returns on stock returns stems not from that of past stock returns. Given the importance of this distinction, it may also be useful to test this inference with a sorting procedure. The methodology we use is a two-step version of the sorting procedure applied in Section 3. First, we sort the stocks into three portfolios based on their past one-year or past two-year stock returns. Next, we sort stocks into nine subportfolios based on their past two-year style returns.

This two-pass sort clearly isolates the effects of style returns from those of stock returns. If the preponderance of mean-reverting loser stocks is driving the abnormal returns of loser styles, then the loser-style/winner-stock portfolio should not achieve abnormal returns. Conversely, if the preponderance of persistent winner stocks is driving the abnormal returns of loser styles then the loser-style/loser-stock portfolio should not register abnormal returns. Analogous reasoning suggests that if the spread in the style return portfolios is generated by a concentration of mean-reverting loser stocks within the loser style, then we should not observe any abnormal profits for the style subportfolio spread within the winner stock portfolio. Similarly, if the spread in the style return portfolios is generated by the greater number of persistent winner stocks within the loser style, then we should not witness any abnormal profits for the style subportfolio spread within the loser stock portfolio.

The results of the two-pass sorts reported in Table 6 indicate that abnormal returns of the loser style and of the spread between the loser and winner styles are not artifacts of variation in loser/winner stock composition in these style portfolios. The three- and four-factor alphas of the loser style are positively significant at the 5% level for five of the six stock return portfolios. Similarly, the three-factor alpha of the style spread is positively significant at the 5% level for five of the six stock return

Table 6
Two-pass sorts on past stock returns and on style returns in the past two years

Stocks are sorted on January 1 each year from January 1984 to December 1999 into three stock portfolios based on their past returns and into nine style subportfolios based on their styles' returns in the last two calendar years. The portfolios are rebalanced monthly so the weights are re-adjusted to equal whenever a stock disappears. Stocks with the lowest past returns comprise portfolio L, stocks with the highest past returns comprise portfolio H, and other stocks comprise portfolio M. Stocks in the style with the lowest past two-year style returns comprise portfolio 1 and stocks in the style with the highest returns comprise portfolio 9. The t-statistics, derived using White (1980) standard errors, are in parentheses. The number of observations for each regression is 192 for all portfolio M and portfolio H regressions. The number of observations for each regression is between 168 to 192 for portfolio L regressions due to missing observations in some years.

Style portfolio	Stock return portfolio (sorted on stock returns in the past year)					
	Portfolio L (lowest stock returns)		Portfolio M		Portfolio H (highest stock returns)	
	Three-factor alpha	Four-factor alpha	Three-factor alpha	Four-factor alpha	Three-factor alpha	Four-factor alpha
Panel A: two-pass sort based on past two-year style return and past year stock returns						
Portfolio 1 (lowest style returns)	0.51	1.02**	0.59**	0.64**	1.34**	1.46**
	(1.49)	(2.89)	(3.14)	(3.32)	(4.83)	(4.87)
Mean number of stocks	*24*	*24*	*33*	*33*	*33*	*33*
Portfolio 9 (highest style returns)	−0.65	−0.01	−0.18	0.02	0.18	0.21
	(−1.63)	(−0.01)	(−0.77)	(0.08)	(0.79)	(0.89)
Mean number of stocks	*23*	*23*	*32*	*32*	*64*	*64*
Spread (portfolio 1–9)	1.37**	1.16	0.77*	0.62*	1.17**	1.25**
	(2.64)	(1.94)	(2.54)	(1.97)	(3.27)	(3.27)
Panel B: two-pass sort based on past two-year style return and past two-year stock returns						
Portfolio 1 (lowest style returns)	0.78*	1.29**	0.62**	0.60**	1.26**	1.40**
	(2.38)	(4.09)	(3.46)	(3.45)	(4.27)	(4.26)
Mean number of stocks	*18*	*18*	*34*	*34*	*39*	*39*
Portfolio 9 (highest style returns)	0.28	0.63	−0.27	−0.08	0.06	0.13
	(0.59)	(1.22)	(−1.20)	(−0.34)	(0.26)	(0.56)
Mean number of stocks	*16*	*16*	*23*	*23*	*60*	*60*
Spread (portfolio 1–9)	0.67	0.85	0.89**	0.68*	1.20**	1.26**
	(1.15)	(1.30)	(2.87)	(2.11)	(3.20)	(3.04)

*Significant at the 5% level.
**Significant at the 1% level.

portfolios, while the four-factor alpha of the style spread is positively significant at the 5% level for four of the six stock return portfolios.

While it is true that the style results are weakest for the portfolio with the loser stocks (portfolio L) in terms of the significance of the alphas, some of the loser style alpha and style spread alpha estimates in Table 6 are actually larger than those in Table 1. For instance, in Table 6 Panel B, the loser style four-factor alpha and the spread's four-factor alpha within the L and H return portfolios (stocks within the lowest and highest 33th percentile respectively) are both larger than their counterparts in Table 1. Also, in Table 6 Panel A, the spread's three-factor alpha and four-factor alpha within the L and H return portfolios, are both larger than the corresponding spreads in Table 1. The spreads in Table 6 suggest that even if we constrain ourselves to either the stocks in the top third of returns or to the stocks in the bottom third of returns, we still get an approximate 12% per annum difference between the stocks in the loser and winner styles.

In the one-pass sort on style returns (Table 1), the average number of stocks in the loser style portfolio and winner style portfolio is 91 and 134, respectively. In the two-pass sort on style returns and stock returns (Table 6), the average number of stocks in the loser style subportfolio ranges from 18 to 39. The average number of stocks in the winner style subportfolio ranges from 16 to 64. Given the reduction in portfolio sample size in Table 6 as a result of the finer, two-pass sort, the resultant decrease in precision comes as no surprise. Also, it is not surprising that the only return portfolio with insignificant three and four-factor spreads is the very same portfolio that has the least stocks (Portfolio L, Panel B).

All in all, the two-pass sort results provide rather convincing evidence that the style reversals are distinct from any stock-level momentum or reversal effects, and nicely complement the cross-sectional results reported in Table 2, which control for stock returns.

5.2. Time-series tests of style momentum

In Sections 4.1 and 4.2, we used a cross-sectional approach to analyze the effects of style returns on stock returns. This cross-sectional approach allows us to control for stock characteristics, ratios, and returns in the most direct fashion. We find weak evidence for style continuations at the quarterly horizon especially with value/growth styles.

In this section, we adopt a time-series approach to further investigate style continuations at quarterly frequencies and to complement the cross-sectional tests in Sections 4.1 and 4.2. The time-series approach allows us to verify whether the relative returns between two pre-specified styles exhibit momentum. However, controlling for stock ratios and characteristics in this context becomes less straightforward. One cannot directly control for the explanatory power of stock characteristics and ratios on the cross-section of returns in a time-series regression of relative returns on their quarterly lags. One indirect way of doing this is to first regress the returns on factors constructed from the stock characteristics and ratios, and then perform time-series analyses on the resultant alphas.

Toward this end, we estimate the following regressions to see if momentum exists with value minus growth return/alpha:

$$vgret_t = a_1 + b_1 vgret_{t-1} + b_2 vgret_{t-2} + b_3 vgret_{t-3} + b_4 vgret_{t-4} + \varepsilon_t, \tag{5}$$

$$\begin{aligned} vgalpha3ff_t = {} & a_1 + b_1 vgalpha3ff_{t-1} + b_2 vgalpha3ff_{t-2} + b_3 vgalpha3ff_{t-3} \\ & + b_4 vgalpha3ff_{t-4} + \varepsilon_t, \end{aligned} \tag{6}$$

$$\begin{aligned} vgalpha4ff_t = {} & a_1 + b_1 vgalpha4ff_{t-1} + b_2 vgalpha4ff_{t-2} + b_3 vgalpha4ff_{t-3} \\ & + b_4 vgalpha4ff_{t-4} + \varepsilon_t, \end{aligned} \tag{7}$$

where $t = 1,\ldots,T$, and $vgret_t$ is the difference between quarterly value return and quarterly growth return in quarter t. Quarterly value return is the average return of small value, mid-cap value, and large value styles. Quarterly growth return is the average return of small growth, mid-cap growth, and large growth styles. The difference between the quarterly value three-factor alpha and quarterly growth three-factor alpha in quarter t is $vgalpha3ff_t$. Quarterly value three-factor alpha is the average three-factor alpha of small value, mid-cap value, and large value styles. Quarterly growth three-factor alpha is the average three-factor alpha of small growth, mid-cap growth, and large growth styles. To obtain a style's three-factor alpha, fund three-factor alphas are estimated over 36-month rolling windows (or over a minimum window of 30 months if the fund has less than 36 months of past return data). The estimates are then averaged over each style to obtain the style alphas. The difference between quarterly value four-factor alpha and quarterly growth four-factor alpha in quarter t is $vgalpha4ff_t$, where the four-factor style alphas are estimated in an analogous fashion to the three-factor style alphas.

Eq. (5) is the basic time-series regression on the value-growth style return. Eq. (6) controls for fundamental risk. Since Barberis and Shleifer (2003) is a positive feedback story at the style level, any momentum effects should persist after controlling for fundamental risk. Eq. (7) controls for stock-level momentum and allows us to further test Barberis and Shleifer's (2003) assertion that style-level momentum is not solely driven by stock-level momentum.

The results reported in Table 7 suggest that style-level momentum exists for the relative performance between value and growth. A one-basis-point increase in value-minus-growth return one quarter ago increases value-minus-growth return by about 0.3 basis points. This effect remains after controlling for the covariation with risk proxies and stock-level momentum. We also estimate the same set of regressions with small-minus-large return/alpha and do not find evidence for momentum at the quarterly horizon. This is consistent with the Barberis and Shleifer (2003) prediction that style momentum should be more pronounced for styles that investors perceive to be better substitutes, since the flow correlation between value and growth styles is much smaller than that between small and large styles.

Table 7
OLS time-series regressions on quarterly value-growth returns and alphas
OLS time-series regressions are estimated on value-growth relative return, and value-growth relative alpha. Value return is the average return of small value, mid-cap value, and large value styles. Growth return is the average return of small growth, mid-cap growth, and large growth styles. Value alpha and growth alpha are calculated analogously. Displayed are the coefficient estimates when value-growth return, Fama and French (1993) three-factor alpha, and Carhart (1997) four-factor alpha are regressed on their respective quarterly lags, i.e., the second column displays the coefficient estimates when value-growth three-factor alpha is regressed on quarterly lags of value-growth three-factor alpha.

Independent variable	Dependent variable = value-growth return/alpha		
	vg return (t)	vg three-factor alpha (t)	vg four-factor alpha (t)
vg return/alpha ($t-1$)	0.31*	0.32*	0.26*
	(2.27)	(2.28)	(2.21)
vg return/alpha ($t-2$)	−0.26	0.04	0.10
	(−1.84)	(0.27)	(0.79)
vg return/alpha ($t-3$)	0.37*	0.07	0.08
	(2.64)	(0.47)	(0.66)
vg return/alpha ($t-4$)	0.12	−0.21	−0.17
	(0.84)	(−1.38)	(−1.37)

*Significant at the 5% level.

6. Conclusion

The study of style investing is at its incipient stages despite the prevalence of style investing in developed financial markets. By looking at the U.S. stock market from the perspective of style investing, we find evidence for style-level reversals, style-level momentum, and positive feedback trading at the style level.

The style value and momentum effects are not driven by stock reversals and continuations. Nor can they be explained by fundamental risk or other stock-level positive feedback trading, learning, or psychological stories. Moreover, these effects are stronger for styles that investors perceive to be better substitutes. This finding is hard to reconcile with any style-level learning or psychological model.

Together, our results are consistent with the style-level positive feedback trading model of Barberis and Shleifer (2003). One caveat is that the style momentum effects uncovered in this paper are much weaker than the style reversal effects. It will be interesting to test whether style momentum manifests more strongly with higher frequency (daily and weekly) data. Other promising avenues for further research include analyzing the returns and flows of pension fund styles, and exploring the value and momentum effects of international fund styles (e.g., Emerging Asia, Emerging Latin America, etc.).

Appendix

This section details the algorithm we use to estimate the equity style of a fund for the fund-years which have missing style information. The algorithm consists of the following sequence of steps in descending order of priority. For example, if a fund has "small cap index" in its name, then we label it as a small-cap blend fund, even if its Strategic Insight code is SCG.

1. Funds classified by Strategic Insight, Wiesenberger, and ICDI as sector funds, bond (including municipals) funds, money market funds, global funds, and international funds are omitted.
2. Funds classified by Strategic Insight as flexible funds (FLX), balanced funds (BAL), principal return funds (EPR), and corporate income mixed funds (IMX) are domestic hybrid funds and are omitted.
3. If a fund name makes explicit reference to the style of stocks the fund invests in, it is assumed to invest in that style, e.g., Consulting Grp Capital Markets Large Cap Value Equity fund is a large-cap value fund. Also, balanced funds are domestic hybrid funds and are omitted. Index funds are blends, e.g., a fund whose name contains "mid-cap index" is a mid-cap blend fund. Funds with "index" but without "mid", "large", or "small" in their names are large blend funds.
4. Funds classified by Strategic Insight as mid-cap growth funds (GMC) are mid-cap growth funds.
5. Funds classified by Strategic Insight as small-cap growth funds (SCG) are small-cap growth funds.
6. Funds classified by Strategic Insight as growth and income funds (GRI) or income and growth funds (ING) are large value funds.
7. Funds classified by Strategic Insight as aggressive growth funds (AGG) are large growth funds.
8. Funds classified by Strategic Insight as growth funds (GRO) are large blend funds.
9. Funds classified by Wiesenberger as stability, income, and growth funds (S-I-G) or income funds (I) are domestic hybrid funds and are omitted.
10. Funds classified by Wiesenberger as growth funds (G) are large growth funds.
11. Funds classified by Wiesenberger as income and growth (I-G) are large blend funds.

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