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Style investing, comovement and return predictability[☆]

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ABSTRACT

Barberis and Shleifer (2003) argue that style investing generates momentum and reversals in style and individual asset returns, as well as comovement between individual assets and their styles. Consistent with these predictions, in some specifications, past style returns help explain future stock returns after controlling for size, book-to-market and past stock returns. We also use comovement to identify style investing and assess its impact on momentum. High comovement momentum portfolios have significantly higher future returns than low comovement momentum portfolios. Overall, our results suggest that style investing plays a role in the predictability of asset returns.

1. Introduction

Barberis and Shleifer (2003) present a parsimonious model in which investors allocate capital based on the relative performance of investment styles. Their model generates a rich set of predictions, some of which have received empirical attention. First, style-level return-chasing behavior generates both style and asset-level momentum. Barberis and Shleifer (2003) argue that the evidence in Moskowitz and Grinblatt (1999), Lewellen (2002), and Haugen and Baker (1996) is consistent with the profitability of style-level momentum (see also Teo and Woo, 2004). Second, they show that style investing generates excess comovement of assets within styles. Consistent with this, Barberis, Shleifer, and Wurgler (2005) show that when a stock is added to the Standard & Poor's 500 index, its comovement with the index increases (see also Greenwood, 2008; Boyer, 2011). Finally, they show that style-based investing can generate momentum in individual asset returns at intermediate horizons and reversals at longer horizons. In their words:

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"If an asset performed well last period, there is a good chance that the outperformance was due to the asset's being a member of a 'hot' style... If so, the style is likely to keep attracting inflows from switchers next period, making it likely that the asset itself also does well next period" (pp. 183–184). It is this hitherto unexplored connection between style investing and asset-level return predictability that we investigate in this paper.

A simple way to test whether style investing is responsible (at least in part) for asset-level return predictability is to see if past style returns have any predictive power in the cross section. We identify styles using the now ubiquitous size and value-growth grids, and then estimate Fama and MacBeth (1973) regressions of future stock returns on size, book-to-market ratios, past stock returns, and past style returns.[2] We find that between 1965 and 2009, over one, three, six and 12-month future return horizons, style returns measured over the prior 12 months are significant predictors of future returns. We subject this basic result to a series of robustness checks. In some (but not all) specifications, style returns measured over the prior six months are also significant predictors. If we construct size breakpoints using NYSE stocks instead of all stocks, the slope coefficients on style returns are similar in magnitude and retain their statistical significance. If we limit our sample to all-but-tiny stocks (those above the 10th percentile in NYSE size), style returns remain statistically significant using 12-month prior style returns. However, if we use six-month prior returns, style returns are important only in explaining longer horizon future returns. We do not find predictability of past style returns among big stocks only (those above the median NYSE size), implying that style returns based on value-growth alone do not help explain cross-sectional variation in returns among large stocks. The slopes on style returns are stronger in the second half of our sample period (1988–2009). Prior to that, the coefficients of past style returns are mostly indistinguishable from zero. In that latter period, which coincides with increased use of size and value categorization in mutual funds and institutional portfolios, the slopes on style returns are large and reliably positive.

Although the Fama-MacBeth regressions are suggestive of the role of style investing, a prediction of Barberis and Shleifer (2003) allows us to specifically identify its impact; namely, that style investing generates not only momentum but also comovement of a stock with its style. Comovement is an outcome of their model-not a primitive, but it serves as a valuable instrument for style investing. It frees us from treating all stocks as equally important to style investors because we can focus on stocks with extreme past returns and use a stock's comovement with its style to refine our assessment of the predictability induced by style investing. An added advantage is that comovement can be measured with precision, particularly compared with other measures of (aggregate) investor sentiment, behavioral biases, or style flows.[3] Therefore, we implement a second set of tests that exploit this metric. If style-based investing generates asset-level momentum and comovement, then one should be able to use comovement to generate variation in momentum profits.[4]

Each month, we sort stocks into deciles (R1 through R10) based on past six-month returns (Jegadeesh and Titman, 1993). In the same month, we measure the comovement of a security with respect to its style by estimating its beta with respect to style returns over the prior three months (similar to Barberis, Shleifer, and Wurgler, 2005). Using these style betas, we independently sort all stocks into comovement terciles (C1 through C3). If the comovement metric is useful, a momentum portfolio that buys high comovement winners and sells high comovement losers should have higher returns than a momentum portfolio that buys low comovement winners and sells low comovement losers over intermediate horizons. We detect a monotonic relation between momentum profits and comovement. For example, for the six-month portfolio formation and evaluation period, the average winner minus loser (R10–R1) monthly portfolio return for the lowest comovement tercile (C1) is 0.71% per month. This increases to 0.96% for the second tercile (C2) and 1.15% for the highest comovement tercile (C3). The difference of momentum returns between C3 and C1 is large: 0.44% per month with a *t*-statistic of 2.98. Estimates of alphas based on the Fama and French (1993) model display a similar pattern. These return differences are generated from both the short and long side of the portfolio strategy. Winner portfolio returns increase and loser portfolio returns decrease as comovement increases.

Our comovement-based tests drop tiny stocks and are robust to using value-weighted returns, dependent sorts, and measuring comovement using various windows, lags, and style cut-offs. Perhaps the most serious concern with the comovement-based tests is that of spurious correlations with other variables known to influence momentum. Size and book-to-market ratios are obvious candidates (Hong, Lim, and Stein, 2000; Lakonishok, Shleifer, and Vishny, 1994; Asness, 1997; Fama and French, 1996). Another possibility

[2] Using size and value-growth grids to identify styles has several advantages. First, they represent a long-standing approach to thinking about investing, dating back to Banz (1979) for size and Graham and Dodd (1934) for value. The proliferation of retail and institutional investment products based on these categories speaks volumes about the importance of these styles. Second, such a style definition is comprehensive and mutually exclusive. It covers the entire spectrum of domestic equities and does so in a way that a security can belong to only one style at a time. Third, such a style categorization is objective, can be replicated, and can be estimated for a long time series.

[3] Baker and Wurgler (2007) point out the difficulties in measuring aggregate sentiment despite attempts by many authors using trades and flows (see, for example, Kumar and Lee, 2006; Frazzini and Lamont, 2008).

[4] Numerous rational and behavioral theories attempt to explain momentum. Examples of the former include Conrad and Kaul (1998), Berk, Green, and Naik (1999), Johnson (2002), and Sagi and Seasholes (2007), in which momentum can arise from (rational) variation in expected returns, endogenously chosen investment expenditures, expected dividend growth rates, and growth options, respectively. Examples of the latter include Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Daniel, Hirshleifer, and Subrahmanyam (2001) in which momentum arises from the price impact of traders who suffer from a particular behavioral bias (such as overconfidence and representativeness).

is that our comovement–momentum relation is just the volume–momentum relation in disguise. The Lee and Swaminathan's (2000) momentum life-cycle hypothesis in which stocks cycle through attention and neglect can be viewed as an asset-level analog of the Barberis and Shleifer (2003) style-level story. Our results might also conceivably be contaminated by the relation between idiosyncratic volatility and returns (Ang, Hodrick, Xing, and Zhang, 2006), or we might be inadvertently double sorting on past returns. We control for all these confounding effects individually through triple-sort procedures and jointly in a regression framework. For the latter, we form portfolios based on the component of comovement that is orthogonal to all these factors (from a first-pass regression). Individual controls sometimes influence the magnitude of the return differences in comovement-based momentum portfolios, but the gist of our results and their statistical significance remains. More important, the component of comovement that is (jointly) orthogonal to all these factors continues to generate economically important and statistically robust results. To us, this suggests that comovement explains variation in momentum beyond spurious correlations with the above variables.

Our tests can never perfectly and precisely pin down whether the return patterns that we find are due to differences in risk or style chasing. Nonetheless, we can provide circumstantial evidence on the issue. The fact that our results are present in both raw returns and alphas suggests that (constant) risk differences are not responsible. We also find similar results in conditional tests in which we allow for time series variation in loadings that changes with the style composition of our portfolios. Moreover, similar to Jegadeesh and Titman (2001) and inconsistent with a simple risk explanation, our portfolios experience return reversals after the first year. If style investing is responsible for the relation between comovement and momentum profits, then the high comovement tercile should experience larger reversals than the low comovement tercile. This is precisely what we find, offering a degree of consistency between long horizon reversals in style returns (Teo and Woo, 2004) and asset-level returns. We also decompose each stock's total return into a style component (by multiplying its style beta with the style return) and a residual and then generate comovement tercile returns based solely on the style component. We find that approximately 50% of the risk-adjusted return difference between high and low comovement portfolios is explained by style effects. In addition, we use deviations of the R^2 of a stock from the long-run mean R^2 of its style (based on the style regressions described earlier) to measure "excess" comovement. Even though such a test has a look-ahead bias, if the long-run average R^2 of a style represents comovement in cash flows or discount rates or both, then positive deviations thereof could be caused by style investing. Using this metric continues to generate return differentials between comovement terciles, again consistent with style investing. Finally, we show that our results cannot be replicated by assigning stocks into arbitrary styles, indicating that we obtain results because our style definitions are followed by investors.

Our results cannot unequivocally reject other stock-specific rational or behavioral explanations for return predictability cited earlier or portfolio-based lead-lag explanations propounded by Lewellen (2002). But we do not seek to, and this inability does not belie the importance of our results. Our purpose is simply to determine if style investing has a role to play in return predictability. Considering the totality of the evidence, that appears to be the case.

The remainder of the paper is organized as follows. Section 2 discusses style definitions. Section 3 contains the Fama-MacBeth tests, and Section 4 shows comovement-based results. Section 5 discusses alternative explanations. Section 6 concludes.

2. Style identification

Identifying styles that investors direct funds into and out of is a prerequisite to measuring the effects of style investing on return predictability. Investors can group stocks into styles based on common characteristics in cash flows, law, markets, or other dimensions to simplify decision making (Mullainathan, 2002). One could imagine a large number of such groupings so it is important that any taxonomic scheme satisfy three conditions: (1) styles must be widely followed by investors, (2) styles must span the asset class (in our case, domestic equity), and (3) styles must be mutually exclusive. The first condition is important because, for style investing to generate return predictability, it must be followed by an economically large fraction of (marginal) investors. The last two conditions are important because the Barberis and Shleifer (2003) model is one of relative style chasing. In their model, spanning the asset class ensures that investors can direct capital into one style by funding it with withdrawals from another. Mutual exclusivity is an empirical convenience—without it, a security that appears in two styles would have two measures of comovement.

These simple criteria naturally point us toward using size and book-to-market ratios (i.e., value-growth orientations) to identify investment styles. This approach is widely used in the investment management community (for example, by mutual funds and pension funds). Empirical evidence on this is provided by Kumar (2009) and Froot and Teo (2008), who show that retail and institutional investors allocate capital at the style level and do so using size and value-growth dimensions. Cooper, Gulen, and Rau (2005) report that some mutual funds strategically change their name to 'hot' styles (in size and value-growth dimension) to successfully attract flows. Boyer (2011) provides evidence that stocks begin to commove more with the S&P Barra value-growth index that they join. In addition, style portfolios generated by this approach span the asset class, and a security classified in a particular style cannot be placed in an alternative style portfolio in the same period.

3. Cross-sectional results

We first test whether style returns have any predictive power in the cross section. We estimate Fama and

MacBeth regressions of future stock returns on size, book-to-market ratios, past stock returns, and past style returns as described below.

3.1. Sample construction

We consider all stocks with shares codes of 10 and 11 trading on the NYSE, Amex, and Nasdaq between January 1965 and December 2009 in the Center for Research in Security Prices (CRSP) database. We merge CRSP data with Compustat information using the LnkHist file provided by Wharton Research Data Services (WRDS), keeping the link between Compustat and CRSP valid for up to one year after the link-end date. We remove links flagged as duplicates.[5]

We calculate and update size and book-to-market ratios as in Fama and French (1992). To assess future returns that start from July of year t to June of year $t+1$, for size, we use the market value of equity at the end of June in year t. To calculate size, we multiply shares outstanding with end of month prices reported by CRSP. To measure book-to-market ratios, we divide book values at fiscal year-end $t-1$ with the market value of equity in December of year $t-1$. We calculate two sets of size breakpoints: using the full set of securities and using only NYSE stocks. NYSE size breakpoints are downloaded from Kenneth French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). For book-to-market breakpoints, we use only the full set of securities. These breakpoints, established at the end of each June, deliver 5×5 size and book-to-market style portfolios. For each style portfolio, we calculate monthly value-weighted style returns using the beginning of month market capitalization of each security in that month.

3.2. Fama and MacBeth regressions

Our first test of return predictability takes the form of Fama and MacBeth (1973) regressions. We consider four holding period returns as our dependent variables: one-month, three-month, six-month and 12-month returns. In calculating multi-month holding period returns, if a stock delists at any time during the holding period, we assume its future (monthly) returns over that holding period are zero. For example, if a stock delists in month 5, we assume the month 6 return is zero and retain the six-month holding period return (computed accordingly). The independent variables consist of the logarithm of size, the logarithm of the book-to-market ratio, and stock and style returns over the prior six and 12 months. We drop negative book-to-market stocks and winsorize size, book-to-market ratio, and past stock returns at the 1% level in each month to avoid the undue influence of outliers. We skip a month between prior and future returns to ensure that microstructure biases do not creep into our tests. This also ensures that our style returns can be calculated well before future returns. The specifications are similar to those of Fama and French (1992) for monthly horizons and Pontiff and Woodgate (2008) for longer horizons.

The regressions are estimated every month. We report average slope coefficients and t-statistics that are corrected for autocorrelation. It is typical to use the overlap in the holding period to determine the number of lags in the correction (Pontiff, 1996), but we are a bit more conservative than that, adding an extra three to six lags, depending on the specification. For each holding period, we report three specifications: (1) a model that includes size, book-to-market ratios, and past stock returns, (2) a model that includes size, book-to-market ratios, and past style returns, and (3) a full model that includes size, book-to-market ratios, past stock, and past style returns. This allows us to see if any of the other slopes are affected by the inclusion of style returns. Table 1 shows the results for these baseline regressions, in which the entire cross section of securities is used in the regressions and style return breakpoints are computed using all stocks. Panels A and B correspond to prior stock and style returns measured over the prior six and 12 months, respectively.

Across most specifications, the slopes on size, book-to-market, and past individual security stock returns follow familiar patterns. Using one-month future returns, the average coefficients on book-to-market are reliably positive. For example, in the specification that uses past six-month stock returns (Panel A), the coefficient on the book-to-market ratio is 0.32 with a t-statistic of 3.68. This is very close to the slope of 0.33 reported by Fama and French (1992, p. 439) and 0.28 reported by Pontiff and Woodgate (2008, p. 932). Similarly, the coefficients on size are negative, and those on past individual stock returns are positive. The average slopes for the same specifications are -0.13 and 0.46, respectively, once again comparable to coefficients reported in other papers. More variation exists in these slopes when the dependent variable is measured over longer horizons, but the pattern is largely similar.

Our primary interest is in the prior style return. In regressions in which we include both the prior stock and style returns, essentially a horse race between the two, the coefficient on style returns is positive and significant for three-, six- and 12-month future horizons. For example, in predicting future three-month returns while measuring stock and style returns over the prior 12 months (Panel B), the coefficients on stock and style returns are 1.27 (t-statistic$=$2.04) and 2.97 (t-statistic$=$3.79), respectively. Notably, the coefficient on prior stock returns is unchanged compared with a specification in which style returns do not appear; in other words, the addition of style returns does not hinder the ability of momentum to predict future returns. Consider, for example, the prototypical horizon evaluated in the momentum literature: six-month future return regressed on six-month prior

[5] We perform two other unreported sampling checks. First, we match CRSP and Compustat data using the linktable on WRDS, retaining returns between link start and end dates. The impact of this alternative matching procedure on our results is small. Second, we eliminate the first two years of Compustat data for every firm to minimize potential selection biases from the way that firms get added to Compustat. Doing so reduces the number of firm-years, makes the results based on six-month returns slightly weaker, but leaves the results based on 12-month returns unchanged.

Table 1

Fama-MacBeth regressions of future stock returns on size, book-to-market, prior stock returns, and prior style returns.

The table shows the average coefficients from Fama-MacBeth regressions of future one-, three-, six-, and 12-month returns on past six- (Panel A) and past 12-month (Panel B) style and stock returns, the log of firm size, and log of book-to-market ratio. Size, book-to-market ratio, and past stock returns are winsorized at the 1st and 99th percentile each month. Stocks with missing or negative book values are not included in the regressions. Stocks are assigned to a style portfolio, which is defined using the intersection of size and book-to-market quintiles from all stocks at the end of June of each year. Monthly style returns are value-weighted returns of all stocks in the style using the beginning of month market capitalization. The sample consists of all NYSE, Amex, and Nasdaq stocks between 1965 and end of 2009. The intercept is included in the regressions, but its coefficient is not reported. We skip a month between the portfolio formation period and the subsequent holding period. t-statistics (in parentheses) are calculated using Newey-West procedures with a lag equal to 4 for one and three-month future returns, 9 for six-month future returns and 18 for 12-month future returns. R^2 is the average adjusted R^2.

Variables	One-month future return			Three-month future return			Six-month future return			12-month future return		
Panel A: Style and stock return regressors measured over prior 6 months												
Style return	—	0.85	0.67	—	4.07	2.98	—	8.66	6.11	—	14.11	10.78
		(1.59)	(1.41)		(3.24)	(2.63)		(3.40)	(2.70)		(3.52)	(2.69)
Stock return	0.46	—	0.47	2.26	—	2.25	5.24	—	5.20	7.13	—	7.04
	(1.76)		(1.80)			(3.2 2)	(3.34)		(3.31)	(3.51)		(3.44)
				(3.22)								
Log size	−0.13	−0.13	−0.13	−0.33	−0.35	−0.37	−0.67	−0.74	−0.78	−1.32	−1.41	−1.46
	(−2.53)	(−2.53)	(−2.68)	(−2.20)	(−2.35)	(−2.54)	(−2.13)	(−2.37)	(−2.59)	(−1.84)	(−1.99)	(−2.14)
Log BM	0.32	0.30	0.29	0.97	0.92	0.86	1.99	1.86	1.71	3.69	3.38	3.22
	(3.68)	(3.52)	(3.41)	(3.87)	(3.68)	(3.46)	(3.95)	(3.76)	(3.54)	(3.58)	(3.37)	(3.29)
R^2	3.32	2.45	3.39	4.34	3.55	4.42	4.72	3.90	4.80	4.81	4.12	4.88
Panel B: Style and stock return regressors measured over prior 12 months												
Style return	—	1.05	0.92	—	3.39	2.97	—	6.65	5.93	—	10.39	9.51
		(3.01)	(3.07)		(3.87)	(3.79)		(4.38)	(4.15)		(4.13)	(3.83)
Stock return	0.41	—	0.40	1.30	—	1.27	2.31	—	2.23	2.71	—	2.59
	(1.90)		(1.86)	(2.11)		(2.04)	(1.71)		(1.63)	(1.75)		(1.67)
Log size	−0.13	−0.14	−0.15	−0.34	−0.37	−0.40	−0.67	−0.72	−0.76	−1.33	−1.38	−1.43
	(−2.60)	(−2.77)	(−2.95)	(−2.25)	(−2.44)	(−2.67)	(−2.07)	(−2.24)	(−2.41)	(−1.802)	(−1.92)	(−2.05)
Log BM	0.34	0.28	0.30	1.07	0.86	0.89	2.15	1.75	1.76	3.88	3.28	3.29
	(4.03)	(3.41)	(3.69)	(4.43)	(3.53)	(3.82)	(4.40)	(3.55)	(3.75)	(3.73)	(3.26)	(3.37)
R^2	3.39	2.45	3.45	4.44	3.55	4.52	4.69	3.89	4.77	4.71	4.11	4.78

Table 2
Fama-MacBeth regressions with style returns computed using NYSE size breakpoints.

The table shows the average coefficients from Fama-MacBeth regressions of future one-, three-, six-, and 12-month returns on past six-month (Panel A) and past 12-month (Panel B) style and stock returns, the log of firm size, and log of book-to-market ratio. Size, book-to-market ratio, and past stock returns are winsorized at the 1st and 99th percentile each month. Stocks with missing or negative book values are not included in the regressions. Stocks are assigned to a style portfolio, which is defined using the intersection of size and book-to-market quintiles at the end of June of each year. Size quintile breakpoints are established using NYSE stocks only. Monthly style returns are value-weighted returns of all stocks in the style using the beginning of month market capitalization. The sample consists of all NYSE, Amex, and Nasdaq stocks between 1965 and end of 2009. The intercept is included in the regressions but its coefficient is not reported. We skip a month between the portfolio formation period and the subsequent holding period. *t*-statistics (in parentheses) are calculated using Newey-West procedures with a lag equal to 4 for one- and three- month future returns, 9 for six-month future returns and 18 for 12-month future returns. R^2 is the average adjusted R^2.

	Future return period			
	One month	Three months	Six months	12 months
Panel A: Style and stock return regressors measured over prior 6 months				
Style return	1.17 (1.97)	3.79 (2.49)	7.66 (2.33)	17.53 (3.04)
Stock return	0.46 (1.77)	2.25 (3.23)	5.22 (3.34)	7.04 (3.46)
Log size	−0.16 (−3.08)	−0.41 (−2.72)	−0.86 (−2.68)	−1.63 (−2.30)
Log BM	0.29 (3.08)	0.89 (3.60)	1.72 (3.55)	3.06 (3.16)
R^2	3.40	4.43	4.82	4.90
Panel B: Style and stock return regressors measured over prior 12 months				
Style return	1.07 (2.66)	3.60 (3.40)	7.72 (3.83)	13.33 (3.77)
Stock return	0.41 (1.92)	1.30 (2.12)	2.30 (1.71)	2.65 (1.71)
Log size	−0.17 (−3.23)	−0.45 (−2.90)	−0.87 (−2.64)	−1.68 (−2.29)
Log BM	0.27 (3.34)	0.82 (3.57)	1.60 (3.40)	2.89 (2.95)
R^2	3.47	4.54	4.80	4.80

returns (Panel B). In this regression, the prior individual stock return has an average slope of 5.24 with a *t*-statistic of 3.34. For the same horizon, the prior style return has a slope of 8.66 with a *t*-statistic of 3.40. When the two appear jointly, in the same regression, the coefficient on the own stock return is largely the same (5.20 with a *t*-statistic of 3.31) and the coefficient on the past style return drops to 6.11 (*t*-statistic=2.70). Some variation in the results emerged depending on the prior return horizon. If we measure prior returns over longer horizons (12 months, as in Panel B), the slopes on stock and style returns are similar to those using prior six-month returns, holding the forecasting horizon constant. However, the slopes on style returns are estimated more precisely. In general, the predictive power of style returns is better when style returns are constructed over the prior 12 months.

One way to put these results in economic perspective is to compare the coefficients of prior stock and style returns, along with their (unconditional) standard deviations. In the regression described above, the style return has a slope that is about 18% larger than that of the stock return (6.11 versus 5.20). In our sample, the time series average of the cross-sectional standard deviation of six-month style returns is 7.8%, compared with an average standard deviation of 32% for individual stocks. Because the standard deviation of style returns is about 24% of that of stock returns (7.8/32), the impact of a 1 standard deviation increase in style returns is about 28% (1.18*0.24) of a 1 standard deviation increase in stock returns. If instead we use past 12-month returns, the economic significance of style returns becomes 68% that of prior stock returns. Clearly, the own-stock momentum effect is larger, but the style-return effect is not insubstantial.

3.3. *Variations in style breakpoints and subsamples*

The style returns used in the above regressions are constructed using a 5×5 grid of size and book-to-market ratios using all stocks. The advantage of this grid is that there are large and roughly the same number of stocks in each style portfolio. However, it is useful to consider other breakpoints that could better proxy for the styles followed by investors. NYSE based breakpoints correlate more closely with the classifications typically employed by investors, at least as constructed by Russell, S&P Barra, and other such organizations.[6] For example, as of July 2009 (using market capitalization at the end of June), our size breakpoints using all stocks are \$42 million, \$145 million, \$421 million, and \$1,532 million. The fraction of total market capitalization in the five size groups is 0.2%, 0.7%, 2.1%, 6.5%, and 90.6%. Clearly, the bottom two quintiles are very small stocks (micro-cap securities), whereas the vast majority of aggregate market capitalization sits in the top quintile. If we use NYSE breakpoints for the same period instead, the breakpoints are \$338 million, \$903 million, \$2,075 million, and \$5,030 million. The fraction of total market capitalization in the five size groups becomes 2.8%, 4.1%, 6.1%, 11.7%, and 75.3%, clearly a better distribution in terms of market capitalization.

In Table 2, we repeat the Fama-MacBeth regressions but with style returns constructed from size breakpoints determined by NYSE stocks. As before, in Panels A and B past style and stock returns are computed over the prior six- and 12-months, respectively. The slopes on past stock returns are virtually unchanged from the specifications reported in Table 1. The slopes on past style returns,

[6] We thank the referee for suggesting this approach.

however, are somewhat higher. For instance, in Panel A, using one-month and six-month future returns as the dependent variable, the coefficient on past six-month style returns is 1.17 and 7.66, respectively. This is higher than the equivalent coefficients of 0.67 and 6.11 reported in Table 1. Similar improvements are evident using style returns constructed over the prior 12 months (Panel B).

As discussed in Section 2, the Barberis and Shleifer (2003) model of style investing that we are interested in is one of relative style investing requiring all styles be included in the asset class. Nonetheless, examining how style return induced predictability varies across subsamples is still interesting. In these subsamples, we can test predictability only within the styles represented.

In Table 3, we eliminate all firms smaller than the 10th percentile in NYSE size cutoffs established at end of each June (so-called tiny firms). We then reestimate the Fama-MacBeth regression for this subsample, using style breakpoints constructed from all stocks (Panel A), as well as NYSE breakpoints (Panel B). When styles are constructed using all stocks in the 5×5 grid, we mechanically lose five styles entirely and another five styles are extremely thinly represented. However, if the NYSE breakpoints are used, we do not mechanically lose any styles. Panel A demonstrates the importance of tiny firms in the sample. When style returns are constructed from past 12-month returns, the slopes on past style returns drop relative to the full sample (Table 1 Panel B) but remains statistically significant. For example, using one-month future returns for the full sample, the average coefficient on past style returns constructed from 12-month returns was 0.92 (t-statistic=3.07). For the all-but-tiny sample, the slope drops to 0.71 with a t-statistic of 2.46. And, for the same sample, if we use

Table 3
Fama-MacBeth regressions on subsamples.

The table shows the average coefficients from Fama-MacBeth regressions of future one-, three-, six-, and 12-month returns on past six- (Panel A) and past 12-month (Panel B) style and stock returns, the log of firm size, and log of book-to-market ratio. Size, book to market ratio and past stock returns are winsorized at the 1st and 99th percentile each month. Stocks with missing or negative book values are not included in the regressions. Stocks are assigned to a style portfolio, which is defined using the intersection of size and book-to-market quintiles at the end of June of each year. In Panels A and C, size quintile breakpoints are established using all stocks. In Panels B and D, size quintile breakpoints are established using NYSE stocks only. Monthly style returns are value-weighted returns of all stocks in the style using the beginning of month market capitalization. The all-but-tiny sample excludes stocks below the 10th percentile in size based on NYSE breakpoints. The big stocks sample includes stocks only larger than the median size based on NYSE breakpoints. The sample period is between 1965 to the end of 2009. The intercept is included in the regressions but its coefficient is not reported. We skip a month between the portfolio formation period and the subsequent holding period. t-statistics (in parentheses) are calculated using Newey-West procedures with a lag equal to 4 for one- and three-month future returns, 9 for six-month future returns and 18 for 12-month future returns. R^2 is the average adjusted R^2.

	Future returns, past 6-month return regressors				Future returns, past 12-month return regressors			
	One month	Three months	Six months	12 months	One month	Three months	Six months	12 months
Panel A: All-but-tiny stocks								
Style return	0.76 (1.63)	1.69 (1.47)	4.36 (2.12)	8.38 (2.06)	0.71 (2.46)	1.77 (2.34)	3.65 (2.62)	7.50 (2.95)
Stock return	0.99 (3.10)	3.23 (3.65)	6.98 (3.54)	10.66 (4.11)	0.70 (2.78)	1.86 (2.53)	3.30 (2.11)	4.71 (2.74)
Log size	−0.04 (−0.84)	−0.13 (−1.11)	−0.34 (−1.35)	−0.73 (−1.30)	−0.04 (−0.97)	−0.16 (−1.28)	−0.35 (−1.36)	−0.78 (−1.41)
Log BM	0.27 (2.99)	0.79 (3.09)	1.65 (3.31)	3.00 (2.98)	0.29 (3.49)	0.89 (3.89)	1.78 (3.88)	2.97 (2.92)
R^2	4.45	5.73	6.16	6.16	4.64	5.96	6.14	5.95
Panel B: All-but-tiny stocks with style returns using NYSE breakpoints								
Style return	0.64 (1.32)	1.65 (1.38)	4.12 (1.67)	10.14 (2.49)	0.62 (2.03)	2.15 (2.66)	4.95 (3.48)	10.61 (4.78)
Stock return	0.98 (3.08)	3.22 (3.64)	6.98 (3.54)	10.64 (4.12)	0.70 (2.79)	1.85 (2.53)	3.29 (2.10)	4.67 (2.71)
Log size	−0.03 (−0.80)	−0.14 (−1.13)	−0.34 (−1.35)	−0.78 (−1.41)	−0.05 (−1.14)	−0.18 (−1.49)	−0.43 (−1.64)	−0.87 (−1.58)
Log BM	0.28 (3.10)	0.85 (3.32)	1.79 (3.60)	3.07 (3.01)	0.31 (3.69)	0.91 (3.94)	1.77 (3.80)	2.84 (2.76)
R^2	4.45	5.74	6.19	6.17	4.64	5.98	6.15	5.95
Panel C: Big stocks								
Style return	0.27 (0.31)	0.63 (0.30)	−0.50 (−0.13)	−6.12 (−1.04)	0.55 (1.12)	−0.19 (−0.14)	−1.75 (−0.67)	−4.54 (−0.94)
Stock return	0.51 (1.31)	2.03 (1.93)	6.04 (2.79)	9.74 (3.36)	0.64 (2.18)	1.70 (2.04)	3.31 (1.97)	4.51 (2.40)
Log size	−0.04 (−1.01)	−0.13 (−1.17)	−0.28 (−1.24)	−0.51 (−0.97)	−0.03 (−0.86)	−0.12 (−1.10)	−0.26 (−1.10)	−0.50 (−0.92)
Log BM	0.20 (2.07)	0.54 (1.98)	1.13 (2.08)	1.92 (1.83)	0.19 (2.07)	0.63 (2.51)	1.27 (2.53)	2.05 (2.04)
R^2	5.46	6.67	7.04	6.76	5.79	7.17	7.27	6.56
Panel D: Big stocks with style returns using NYSE breakpoints								
Style return	1.04 (1.89)	3.20 (2.36)	5.61 (2.29)	4.77 (1.23)	0.51 (1.41)	1.05 (1.08)	1.83 (1.05)	2.19 (0.69)
Stock return	0.49 (1.27)	2.01 (1.91)	6.03 (2.78)	9.76 (3.36)	0.64 (2.19)	1.72 (2.07)	3.34 (2.00)	4.57 (2.43)
Log size	−0.02 (−0.60)	−0.11 (−1.03)	−0.28 (−1.31)	−0.49 (−0.99)	−0.04 (−0.93)	−0.15 (−1.32)	−0.34 (−1.50)	−0.54 (−1.06)
Log BM	0.17 (1.76)	0.49 (1.80)	1.01 (1.88)	1.62 (1.46)	0.20 (2.23)	0.59 (2.39)	1.11 (2.24)	1.64 (1.54)
R^2	5.42	6.64	7.03	6.71	5.78	7.17	7.28	6.55

NYSE breakpoints to construct style returns, the slope is 0.62 with a t-statistic of 2.03. When style returns are constructed from past six-month returns, the slope on style returns is indistinguishable from zero for one- and three-month future returns. The slopes are positive and at least 2 standard errors different from zero at longer (six- and 12-month) horizons. If we use NYSE breakpoints to construct style returns (Panel B), the slopes are only significant at the 12-month horizon. Given these results, we conclude that excluding tiny firms reduces the ability of style returns to predict future returns at shorter horizons. At longer horizons, the coefficient of style returns is significant but diminished somewhat in magnitude.

We also estimate similar regression for firms above the median NYSE size (big firms). These are also reported in Panels C and D of Table 3, corresponding to style returns constructed using all stocks and NYSE breakpoints, respectively. In this sample, style returns have no role to play, regardless of how they are constructed (using all stocks or NYSE breakpoints) and irrespective of future return horizons. Here we have to be a bit more careful in interpretation of the style return coefficients. Restricting the sample to big firms causes us to eliminate 15 out of the 25 style return quintiles, and another five quintiles are very thinly represented when styles are constructed using all stocks. When using NYSE breakpoints, ten styles are mechanically eliminated and five styles are relatively thinly represented. This means that our style return variable is only capturing variation in styles in the value-growth dimension within big stocks. In other words, in big stocks, style investing along value–growth dimensions (i.e., style switching between large value and large growth) generates no predictability in individual stock returns. This could be because style investing has no effect among large stocks or because style investors switch not only across book-to-market dimension but also across size and book-to-market simultaneously. For example, if investors switch between small-growth and large-value, we might not be able to capture this effect among large stocks only.

In Table 4, we examine the coefficients on style returns in two subperiods. Our interest in this is driven by the notion that the identification of styles with size and value-growth grids is a relatively recent phenomenon. For instance, Morningstar, a compiler of mutual fund information widely followed by investors, moved from classifying funds using growth, growth and income and other such categories to size- and value–growth-based categories in 1992. We split the time series into two roughly equal subperiods and show style return average coefficients and t-statistics for each subperiod for all of the above specifications (combinations of horizons, subsamples, and breakpoints). The results are telling. Regardless of whether we use all stocks or NYSE size breakpoints and irrespective of horizon, style return coefficients are larger in the second half of the sample period. The differences between the subperiods are more striking when we use NYSE breakpoints. Consider, for example, the six-month forward return specification using NYSE breakpoints and past 12-month returns. The average style return coefficient in the full sample period (from Table 2)

Table 4
Fama – MacBeth regressions in subperiods and subsamples.
The table shows the average coefficients on style returns in two subperiods from the Fama-MacBeth regressions, in which future one-, three-, six-, and 12-month returns are regressed on past six- (Panel A) and past 12-month (Panel B) style and stock returns, the log of firm size, and log of book-to-market ratio. Size, book-to-market ratio, and past stock returns are winsorized at the 1st and 99th percentile each month. Stocks with missing or negative book values are not included in the regressions. Stocks are assigned to a style portfolio, which is defined using the intersection of size and book-to-market quintiles at the end of June of each year. In Panel A, size quintile breakpoints are established using all stocks. In Panel B, size quintile breakpoints are established using NYSE stocks only. Monthly style returns are value-weighted returns of all stocks in the style using the beginning of month market capitalization. The all-but-tiny (ABT) sample excludes stocks below the 10th percentile in size based on NYSE breakpoints. The big stocks sample includes only stocks larger than the median size based on NYSE breakpoints. The intercept is included in the regressions but its coefficient is not reported. We skip a month between the portfolio formation period and the subsequent holding period. t-statistics (in parentheses) are calculated using Newey-West procedures with a lag equal to 4 for one- and three-month future returns, 9 for six-month future returns and 18 for 12-month future returns.

	Subperiod 1965–1987				Subperiod 1988–2009			
Sample, Past Horizon	One month	Three months	Six months	12 months	One month	Three months	Six months	12 months
Panel A: Size breakpoints using all stocks								
All stocks, 6	0.01 (0.03)	0.54 (0.42)	1.46 (0.62)	3.27 (0.80)	1.37 (1.69)	5.57 (3.03)	11.10 (2.98)	19.04 (2.94)
All stocks, 12	0.56 (1.63)	1.61 (1.66)	2.70 (1.89)	6.52 (2.80)	1.30 (2.63)	4.42 (3.63)	9.41 (3.99)	12.80 (2.95)
ABT, 6	−0.23 (−0.40)	−1.15 (−0.87)	−0.99 (−0.54)	0.10 (0.03)	1.81 (2.52)	4.70 (2.60)	10.11 (2.92)	17.49 (2.61)
ABT, 12	0.19 (0.64)	0.51 (0.65)	1.29 (1.20)	4.81 (1.87)	1.25 (2.55)	3.11 (2.40)	6.19 (2.43)	10.47 (2.38)
Big, 6	1.35 (1.31)	1.91 (0.92)	0.95 (0.27)	−6.00 (−0.96)	−0.88 (−0.63)	−0.73 (−0.20)	−2.06 (−0.29)	−6.26 (−0.61)
Big, 12	−0.20 (−0.41)	−2.01 (−1.35)	−4.12 (−1.39)	−5.35 (−0.95)	1.34 (1.55)	1.75 (0.76)	0.79 (0.18)	−3.65 (−0.45)
Panel B: Size breakpoints using NYSE stocks								
All stocks, 6	−0.44 (−0.68)	−1.08 (−0.68)	−0.36 (−0.13)	1.69 (0.36)	2.86 (2.97)	8.97 (3.66)	16.28 (2.88)	34.95 (4.01)
All stocks, 12	0.37 (0.82)	1.50 (1.26)	3.12 (1.55)	5.88 (1.63)	1.80 (2.73)	5.83 (3.36)	12.66 (3.82)	21.53 (3.97)
ABT, 6	−0.99 (−1.70)	−2.98 (−2.19)	−5.43 (−2.51)	−4.50 (−1.57)	2.35 (3.32)	6.56 (3.77)	14.38 (4.00)	26.22 (5.11)
ABT, 12	−0.19 (−0.59)	−0.03 (−0.04)	0.68 (0.58)	5.02 (2.72)	1.48 (2.86)	4.48 (3.45)	9.54 (4.10)	16.75 (4.84)
Big, 6	0.20 (0.32)	0.47 (0.33)	−0.28 (−0.11)	−1.02 (−0.25)	1.92 (2.14)	6.09 (2.68)	11.93 (2.99)	11.15 (1.75)
Big, 12	−0.13 (−0.31)	−0.70 (−0.64)	−0.60 (−0.27)	1.22 (0.29)	1.19 (2.02)	2.89 (1.84)	4.44 (1.68)	3.26 (0.68)

was 7.72 with a t-statistic of 3.83. In the 1965–1987 subperiod, that coefficient is 3.12 with a t-statistic of 1.55, but between 1988 and 2009, it is 12.66 with a t-statistic of 3.82. These results are consistent with sustained increase in importance of mutual funds and institutional portfolios that use size and value approaches to designate their strategies.

4. Style investing, comovement, and momentum

The regressions describe above are suggestive. Style returns apparently have some role to play in predictability overall, but not much among big stocks. We can, however, lean on specific aspects of theory to design tests that are more closely tied to the theory. In the Barberis and Shleifer (2003) model, all stocks are correctly classified into styles and, within a style, all stocks are subject to the same level of style investor flows. Therefore style chasing per se generates stock-level predictability and no variation exists among individual stocks that belongs to the same style. However, one might reasonably hypothesize that stocks that are more closely identified with a particular style might be more sensitive to the effects of style chasing. Such a story provides a role for a style beta [or, in the language of Barberis and Shleifer (2003), the comovement of a stock with its style] in getting a better handle on predictability. The existing empirical evidence (Barberis, Shleifer, and Wurgler, 2005; Greenwood, 2008; Green and Hwang, 2009; Boyer, 2011) suggests a relevant role for comovement. If style-based investment generates asset-level predictability and momentum, then we should be able to use comovement to generate variation in momentum profits.

4.1. Methods

We follow standard approaches in the momentum literature. Following Jegadeesh and Titman (2001), we exclude stocks that are in the lowest size decile (based on NYSE breakpoints) and those under \$5 at the time of portfolio formation. This is similar to the all-but-tiny sample used in Fama-MacBeth regressions, with the added low price restriction. For momentum portfolio assignments, at the end of each month, we rank stocks based on their prior J period return (for $J=3$, 6, and 12) and then sort stocks into deciles based on these rankings.[7] In the interest of brevity, however, most our tables and discussion focus on portfolios formed on prior six-month returns. For comovement portfolio assignments, we estimate the style beta from the following univariate regression of daily stock returns on the daily style returns (Vijh, 1994; Barberis, Shleifer, and Wurgler, 2005).

$$R_{ist} = a + \beta_{is} R_{st} + \varepsilon, \tag{1}$$

where R_{ist} is the return of stock i belonging to style s on day t and R_{st} is the value-weighted return of the style on day t. Unlike the Fama-MacBeth regressions described in Section 3, we exclude stock i in calculating the return of the style portfolio (R_s) to avoid any mechanical correlation between stock i and the style portfolio. We use the past three months of daily returns as the estimation window and require each stock to have at least 20 return observations. The regression is estimated rolling forward one month at a time generating time series estimates of β_{is}. If a stock changes style at the end of June, its comovement is calculated with respect to the past returns of its new style. Additions or deletions of new stocks to a style affect only future (not past) style returns. Using β_{is}, we sort all stocks into three comovement portfolios (C1, C2, and C3), where C3 is the tercile with the highest comovement. This sorting procedure, which is not within but across styles, captures more stocks in high comovement terciles from styles that have higher variation in betas. Stocks that are miscategorized by us into the wrong style (i.e., stocks that are not followed by style investors for that style) are likely to have low β_{is} and to be allocated to C1. This increases the error in C1 (but not in C3), biasing us against finding differences between C1 and C3 and rendering our results conservative.

Some comments on the use of β_{is} are in order. We measure total comovement, which can be generated by style investing, or common shocks, or both. The two can be disentangled in a couple of ways. First, a relatively precise approach is to use changes in comovement when an exogenous event influences style investment but not cash flows or discount rates. Barberis, Shleifer, and Wurgler (2005) and Greenwood (2008) follow such an identification strategy. But this event-study method is not suited to our research design. From a practical perspective, shocks to cash flows and discount rates are not objectively and frequently observable for a large cross section and time series, and they are rarely exogenous. Second, one could specify a model for expected comovement and examine deviations from expectations. That is a task fraught with potential problems and the outcome of which is subject to a joint testing problem. However, in later tests we attempt to measure excess comovement by examining deviations of a stock's R^2 from the long-run mean R^2 of its style. Such an approach has a look-ahead bias, so we treat that test with some circumspection and view it as a robustness check. Given these difficulties, for the majority of the paper, we work with an unbiased measure of total comovement, β_{is}.

Our primary portfolios of interest are those at the intersection of the extreme loser (R1) and winner portfolios (R10) with low and high comovement terciles (C1 and C3, respectively).[8] Each portfolio is held for K periods following the ranking month (where $K=3$, 6, and 12). As in Jegadeesh and Titman (1993, 2001), we use

[7] An equivalent approach would be to construct portfolio weights using the approach in Lo and MacKinlay (1990), Conrad and Kaul (1998) and Lewellen (2002). We use the simpler decile approach of Jegadeesh and Titman (1993) because it allows us to easily splice momentum deciles with comovement terciles and compare our results with theirs.

[8] We use terciles for comovement to ensure that we have an adequate number of securities in each intersection portfolio. The number of securities in each of our portfolios ranges from 50 to one hundred depending on the subperiod. Our results are robust to the use of comovement quintiles instead of terciles.

overlapping portfolios and assign equal weights to each month in calculating portfolio returns.

4.2. Portfolio statistics

In Table 5, we report various attributes of securities that fall into each comovement tercile separately for losers (Panel A) and winners (Panel B). The first two columns of the table report the average β_{is} and R^2 [both are from the regression in Eq. (1)] within each tercile. Not surprisingly, because comovement terciles are formed based on β_{is}, the average β_{is} increases across terciles from a low of 0.24 to a high of 1.60. Similarly, average R^2 also increases across terciles. Average size of firms increases from C1 to C3 portfolio both on the winner and loser sides. This means that our momentum portfolio based on C3 has on average larger stocks compared with a momentum portfolio based only on past returns. Book-to-market ratio increases slightly on the winner side and decreases on the loser side from C1 to C3.

The remaining columns show average idiosyncratic volatility (with respect to the Fama and French three-factor model), price, volume, turnover, and a Herfindahl Index of industry concentration (based on ten industry definitions from Kenneth French's website). High comovement terciles have slightly lower average prices, but the differences are not monotonic or alarming. In general, the average Herfindahl Index across comovement terciles is comparable and close in value to that obtained in random portfolios (0.16). There are large differences across comovement portfolios in trading activity (volume and turnover) and idiosyncratic volatility. This is also evident in the pairwise correlations reported in Panel C. But we expect this correlation ex ante. Style investing should, by definition, generate large amounts of trading, and this would be reflected in both turnover and volatility. Given the above correlations, in future tests, we control for correlations between comovement, size, book-to-market, volume, turnover, and idiosyncratic volatility.

4.3. Return evidence

Table 6 contains the primary evidence on comovement and momentum. The portfolio formation period is always the prior six months, and we skip a month before examining returns over three holdings periods ($K=3$, 6, and 12 months). We show returns and three-factor alphas for equal-weighted (Panel A) and value-weighted (Panel B) long–short (R10–R1) portfolios in each comovement tercile, as well as the difference between the extreme comovement terciles (C3–C1). We also report separate returns for winners and losers.

For every portfolio evaluation horizon, average momentum returns and alphas increase from C1 to C3. As shown in Panel A, for the commonly examined $J, K=6$ horizon, the equal-weighted average return for long–short portfolios increases from 0.71% per month in C1 to 1.15% in C3. There are similar increases for alphas between C1 and C3. The differences in these returns and alphas, 0.44% and 0.44% per month, have t-statistics of

Table 5
Stock characteristics for terciles formed on comovement.

We estimate the β_{is} of each security with respect to its style portfolio (determined by size and book-to-market) according to the regression equation $R_{ist}=\alpha_i+\beta_{is}R_{st}+\varepsilon_i$ where R_{ist} is the return on stock i at time t and R_{st} is the return on the size and book to market portfolio (style portfolio) that the stock belongs to at time t. R_{ist} is constructed for each i after removing R_i from the matching style portfolio. The regression is estimated using three months of daily returns and rolled forward each month, producing a time series of comovement measures. Each month, all stocks are sorted into terciles (C1, C2, and C3) based on their β_{is}. Then we independently sort stocks into momentum deciles based on their past six-month returns. Panel A reports the summary statistics of the portfolios formed at the intersection of R1 (loser) momentum decile and comovement terciles.. Panel B reports the summary statistics of the portfolios formed at the intersection of R10 (winner) momentum decile and comovement terciles. Panel C reports pairwise correlations of β_{is} with stock characteristics. All summary statistics are averages for the entire sample period. The sample consists of all NYSE, Amex, and Nasdaq stocks between 1965 and 2009, excluding stocks in the smallest NYSE size decile and stocks under \$5 at the time of portfolio formation, and stocks without valid book-to-market ratios at the end of June of each year. R^2 is from the style regression above. Size is the market capitalization at the time of portfolio formation (updated monthly), and book-to-market value is calculated as in Fama and French (1992). Volume and turnover are measured every month. We calculate turnover similar to Lee and Swaminathan (2000) as the average daily turnover in the past 6 months, where daily turnover is the ratio of number of shares traded each day to the number of shares outstanding at the end of the day. Volume is the average of monthly trading volume for the last three months. Idiosyncratic volatility is calculated with respect to Fama-French three factors for the previous three months as in Ang, Hodrick, Xing, and Zhang (2006). Industry Herfindahl Index is calculated monthly for each portfolio by categorizing firms into ten industries based on industry definitions from Kenneth French's website. A random portfolio has expected mean Herfindahl Index of 0.16.

	Comovement measures		Portfolio statistics						
	β_{is}	R^2	Size (millions)	Book-to-market	Volume (millions)	Turnover	Idiosyncratic volatility	Price	Industry Herfindahl Index
Panel A: Statistics for R1 (losers)									
C1 (Low)	0.24	0.04	981	0.65	1.75	0.0059	0.026	19.47	0.20
C2	0.79	0.12	1,238	0.64	2.01	0.0065	0.027	19.53	0.19
C3 (High)	1.60	0.22	1,369	0.61	4.28	0.0104	0.034	17.85	0.23
Panel B: Statistics for R10 (winners)									
C1 (Low)	0.26	0.06	1,499	0.74	2.77	0.0058	0.024	50.71	0.20
C2	0.80	0.14	1,727	0.77	2.97	0.0064	0.024	49.42	0.19
C3 (High)	1.58	0.22	2,168	0.82	6.07	0.0093	0.029	35.61	0.20
Panel C: Pairwise correlations									
β_{is}	1.00	0.56	0.04	0.01	0.10	0.27	0.24	−0.01	—

Table 6
Monthly returns and three-factor alphas for momentum and comovement based portfolios.

The table shows monthly returns and three-factor Fama-French alphas for long–short (R10–R1), winner R10, and loser R1 portfolios in each comovement tercile over three-, six and 12-month post portfolio formation holding periods (K). The sample consists of all NYSE, Amex, and Nasdaq stocks between 1965 and 2009, excluding stocks in the smallest NYSE size decile and stocks under $5 at the time of portfolio formation, and stocks without valid book to market ratios in June of each year. Sample stocks are independently ranked into deciles (R1 through R10) based on returns over the prior six months ($J=6$) and into comovement terciles (C1 through C3) based on β_{is}, calculated as described in Table 5. We skip a month between the portfolio formation period and the holding periods (K). t-statistics appear in parentheses.

	Holding period: Three months ($K=3$)				Holding period: six months ($K=6$)				Holding period: 12 months ($K=12$)			
	C1	C2	C3	C3–C1	C1	C2	C3	C3–C1	C1	C2	C3	C3–C1
Panel A: Equally weighted long–short (winners–losers) momentum portfolio profits												
Winner–loser returns	0.64	0.93	1.10	0.45	0.71	0.96	1.15	0.44	0.47	0.62	0.73	0.26
	(3.06)	(3.96)	(4.15)	(2.57)	(3.67)	(4.54)	(4.84)	(2.98)	(3.02)	(3.70)	(3.80)	(2.24)
Winner–loser alphas	0.87	1.14	1.31	0.44	0.94	1.19	1.38	0.44	0.72	0.89	1.02	0.30
	(4.14)	(4.92)	(4.85)	(2.39)	(4.79)	(5.74)	(5.79)	(2.91)	(4.72)	(5.44)	(5.43)	(2.47)
Loser returns	0.64	0.57	0.41	−0.23	0.64	0.59	0.40	−0.24	0.75	0.74	0.56	−0.19
	(2.20)	(1.76)	(1.07)	(−1.33)	(2.26)	(1.85)	(1.05)	(−1.52)	(2.73)	(2.37)	(1.52)	(−1.29)
Loser alphas	−0.56	−0.66	−0.83	−0.26	−0.59	−0.67	−0.87	−0.28	−0.46	−0.51	−0.72	−0.26
	(−4.10)	(−4.27)	(−4.33)	(−1.75)	(−4.60)	(−4.73)	(−4.81)	(−2.02)	(−4.11)	(−4.13)	(−4.53)	(−2.15)
Winner returns	1.28	1.50	1.51	0.22	1.36	1.55	1.55	0.19	1.22	1.36	1.29	0.07
	(5.21)	(5.50)	(4.50)	(1.36)	(5.57)	(5.74)	(4.63)	(1.26)	(5.16)	(5.06)	(3.88)	(0.54)
Winner alphas	0.31	0.48	0.49	0.17	0.35	0.51	0.51	0.16	0.26	0.37	0.30	0.04
	(2.60)	(4.35)	(3.59)	(1.20)	(3.30)	(5.43)	(4.41)	(1.30)	(3.24)	(4.93)	(3.05)	(0.38)
Panel B: Value weighted long−short (winners–losers) momentum portfolio profits												
Winner–loser returns	0.34	0.51	0.86	0.52	0.44	0.69	1.01	0.57	0.27	0.47	0.64	0.37
	(1.38)	(1.90)	(3.03)	(2.08)	(2.08)	(3.00)	(4.05)	(2.82)	(1.56)	(2.60)	(3.14)	(2.41)
Winner–loser alphas	0.55	0.65	1.06	0.50	0.69	0.89	1.22	0.53	0.56	0.73	0.95	0.39
	(2.26)	(2.27)	(3.47)	(1.91)	(3.38)	(3.64)	(4.68)	(2.56)	(3.40)	(4.05)	(4.75)	(2.49)
Loser returns	0.72	0.71	0.33	−0.39	0.69	0.65	0.28	−0.41	0.73	0.73	0.42	−0.31
	(2.53)	(2.29)	(0.91)	(−1.69)	(2.54)	(2.19)	(0.80)	(−2.08)	(2.85)	(2.55)	(1.25)	(−1.83)
Loser alphas	−0.38	−0.36	−0.71	−0.33	−0.45	−0.46	−0.80	−0.35	−0.40	−0.39	−0.71	−0.31
	(−2.15)	(−1.88)	(−3.38)	(−1.63)	(−2.88)	(−2.66)	(−4.15)	(−1.94)	(−3.01)	(−2.74)	(−4.33)	(−2.05)
Winner returns	1.06	1.22	1.20	0.13	1.12	1.34	1.29	0.16	1.00	1.20	1.06	0.07
	(4.85)	(4.74)	(3.83)	(0.65)	(5.55)	(5.48)	(4.15)	(0.85)	(5.17)	(5.11)	(3.49)	(0.39)
Winner alphas	0.17	0.29	0.34	0.17	0.24	0.42	0.42	0.18	0.16	0.34	0.24	0.08
	(1.31)	(2.05)	(2.09)	(0.89)	(2.26)	(4.02)	(3.04)	(1.11)	(1.90)	(4.38)	(2.15)	(0.66)

2.98 and 2.91, respectively. The results are similar over portfolio formation and evaluation horizons of under six months (J, $K \leq 6$) and, as is typical for momentum strategies, weaken over longer evaluation horizons ($K=12$). Value-weighted raw returns and alpha differences between C1 and C3 reported in Panel B are higher than those based on the equal-weighted strategy. For J, $K=6$ the return difference between C1 and C3 is 0.57% with a t-statistic of 2.82 (compared with 0.44% for equal-weighted returns). The effect we find seems to be stronger among larger momentum stocks. The long and short sides of the strategy are not individually significant but are so jointly; in other words, the difference in profits between C1 and C3 is generated by both the long and short side.

A difference in monthly alphas of 0.44% is economically large and practically important, corresponding to about 5.4% per year. Even if we compare the improvement in returns from implementing a trading strategy based on C3 with average momentum returns, the improvement is substantial and statistically significant (0.15% per month with a t-statistic of 2.56). More important, these results imply a role for comovement in understanding predictability.

4.4. Robustness

This section describes a battery of robustness tests as well as checks to ensure that our results are not explained by variables that are known to be correlated with momentum profits.

4.4.1. Basic tests

Independent sorts can result in unequal numbers of securities in portfolios, especially if a correlation exists between comovement and past returns. To ensure that this does not influence our results, we also perform dependent sorts. We first sort on J period returns and then, within each momentum decile, sort stocks into comovement terciles with equal numbers of securities. Average monthly returns and alphas from such dependent sorts are shown in Panel A of Table 7 for all three evaluation horizons. In general, the difference between the results based on independent sorts (Table 6) and those based on dependent sorts (Panel A, Table 7) is very small, between 0 and 6 basis points per month.

One might be concerned that our results are sensitive to the way we estimate β_{is}. First, we reestimate β_{is} using a six-month estimation window to ensure that our results are not driven by horizon choice. Panel B shows that, for J, $K=6$, the spread in returns between C1 and C3 remains unchanged at 0.44% per month. Second, if small infrequently traded stocks react to style-based flows with a delay, β_{is} could be affected. To determine if that is the case, we include one-day, one-week, and two-week lagged style returns in our comovement regressions as additional independent variables (Dimson, 1979). The comovement measure then is the sum of betas with respect to contemporaneous style and lagged style returns. We replicate our results using these revised estimates of β_{is} and show them in Panel C. With a one-day lag, the results are very similar to those reported earlier. The spread in returns between C1 and C3 shrinks as the lag length increases. With a one-week lag, the spread in returns between C1 and C3 becomes 0.32%. But in all cases, the spread remains positive and statistically significant.

In Panel D, we present results for the three subperiods. These three subperiods correspond to the original Jegadeesh and Titman (1993) sample period of 1965–1989, the out-of-sample test period of 1990–1998 in Jegadeesh and Titman (2001), and the last holdout period of 1999–2009. The average difference in monthly returns between the C1 and C3 portfolios is 0.34% with a t-statistic of 2.05 in the first subperiod. The estimated monthly alpha is similar (0.33%) but has a t-statistic of 1.92. In the second subperiod, the improvement in returns from incorporating comovement is much larger. For instance, the alpha of the C3–C1 portfolio rises to 0.73% and is highly statistically significant. There is some decline in the ability of comovement to generate statistically significant dispersion in momentum returns in the last subperiod (1999–2009). In unreported results, we show that momentum returns in this last subperiod have much larger standard deviations (this is also easily discernable by examining momentum factors reported on Kenneth French's website). For instance, in the second subperiod, the standard deviation of momentum returns was 4.95% but, in the third subperiod, the standard deviation is 8.15%. Because momentum profits are noisier (and not statistically significant) in this last subperiod due to extreme observations around the market crash in 2001 and market turmoil in 2008 and 2009, it is perhaps not surprising that comovement terciles do not generate statistically significant dispersion in momentum returns either.

Our portfolios are formed from breakpoints created using the full set of eligible securities. We also generate results using NYSE-only breakpoints that are reported in Panel E. For the J, $K=6$ horizon, the average return for long–short portfolios increases from 0.66% per month in C1 to 1.44% in C3. The difference in returns is 0.53% with a t-statistic of 3.44. Panel E indicates that our results are not as sensitive to choice of breakpoints as the Fama-MacBeth regressions.

Finally, Cooper, Gutierrez, and Hameed (2004) show that momentum returns are positive when market returns are positive (up markets) and negative when market returns are negative (down markets). To determine if this influences our results, we follow Cooper, Gutierrez, and Hameed (2004) and define up (down) markets based on market returns over the prior 24 or 36 months and then replicate our results. Although not reported in tables, we find that the difference between the C3 and C1 terciles is higher in up markets but not statistically different from that in down markets.

4.4.2. Spurious correlations

Although such robustness checks are important, perhaps a more fundamental concern is that our results could be generated by a variety of variables that are known to be correlated with momentum profits, not style investing per se. There are several such variables. Notwithstanding the value-weighted results, described above, size is an obvious possibility. In addition, Lakonishok, Shleifer, and Vishny (1994), Fama and French (1996), Asness (1997),

Table 7
Momentum and comovement based portfolios: robustness tests.

The table includes various robustness tests of results in Table 6, Panel A. In Panel A, stocks are first ranked into deciles (R1 through R10) based on returns over the prior $J=6$-month period and then, within each momentum decile, into comovement terciles (C1 through C3) based on β_{is}, calculated as described in Table 5. In Panel B, we calculate β_{is}, (comovement) over the past six months (instead of three months as in the rest of the paper). In Panel C, we follow Dimson (1979) and include one-day, one-week, and two-week lagged style returns as additional independent variables while estimating comovement β_{is} as the sum of betas with respect to style return and lagged style return. In Panel D, the results for $J=6$, $K=6$ portfolio formation and evaluation horizons are presented for the three separate subperiods. In Panel E, the cutoffs for style assignments are based on NYSE breakpoints, instead off full sample breakpoints. Each panel shows monthly returns and three-factor Fama-French alphas for long–short (R10–R1) portfolios in each comovement tercile over various post portfolio formation holding periods (K). t-statistics appear in parentheses.

	C1	C2	C3	C3–C1	C1	C2	C3	C3–C1	C1	C2	C3	C3–C1
Panel A: Portfolios formed with dependent sorts												
	($K=3$)				($K=6$)				($K=12$)			
Returns	0.73 (3.26)	1.04 (3.93)	1.11 (3.76)	0.38 (2.21)	0.79 (3.87)	1.06 (4.47)	1.17 (4.43)	0.38 (2.56)	0.52 (3.23)	0.70 (3.73)	0.72 (3.33)	0.20 (1.67)
Alphas	0.92 (4.14)	1.23 (4.69)	1.35 (4.57)	0.43 (2.46)	1.00 (4.82)	1.28 (5.42)	1.43 (5.41)	0.44 (2.82)	0.75 (4.62)	0.96 (5.16)	1.03 (4.85)	0.28 (2.27)
Panel B: β_{is}, (comovement) estimated over prior six months												
	($K=3$)				($K=6$)				($K=12$)			
Returns	0.55 (2.44)	0.90 (3.82)	1.08 (4.11)	0.53 (2.82)	0.72 (3.62)	0.86 (4.13)	1.16 (4.87)	0.44 (2.84)	0.49 (3.13)	0.57 (4.41)	0.72 (3.74)	0.23 (1.90)
Alphas	0.80 (3.58)	1.16 (5.04)	1.28 (4.79)	0.48 (2.43)	0.96 (4.75)	1.12 (5.54)	1.39 (5.86)	0.44 (2.69)	0.74 (4.82)	0.85 (5.34)	1.01 (5.39)	0.27 (2.12)
Panel C: β_{is}, (comovement) calculated using Dimson (1979) for J, K=6												
	One-day lag				One-week lag				Two-week lag			
Returns	0.76 (3.66)	0.98 (4.71)	1.16 (4.85)	0.40 (3.02)	0.81 (3.69)	1.00 (4.62)	1.13 (4.74)	0.32 (2.97)	0.93 (4.25)	0.94 (4.11)	1.11 (4.62)	0.18 (1.89)
Alphas	0.96 (4.50)	1.17 (5.58)	1.42 (5.84)	0.46 (3.27)	1.06 (4.70)	1.23 (5.57)	1.39 (5.83)	0.33 (2.98)	1.17 (5.29)	1.17 (5.02)	1.37 (5.73)	0.21 (2.01)
Panel D: Subperiod results with portfolios formed and evaluated for J,K=6												
	1965–1989				1990–1998				1999–2009			
Returns	0.87 (3.64)	1.19 (5.26)	1.21 (5.17)	0.34 (2.05)	0.94 (3.14)	1.32 (3.98)	1.63 (4.10)	0.69 (2.37)	0.22 (0.41)	0.16 (0.25)	0.61 (0.79)	0.39 (0.92)
Alphas	1.10 (4.36)	1.42 (6.19)	1.43 (6.06)	0.33 (1.92)	0.93 (3.59)	1.32 (4.36)	1.66 (4.87)	0.73 (2.73)	0.27 (0.56)	0.15 (0.26)	0.54 (0.74)	0.27 (0.63)
Panel E: Cutoffs based on NYSE breakpoints, with portfolios formed and evaluated for J = 6 and K=3, 6, 12												
	($K=3$)				($K=6$)				($K=12$)			
Returns	0.53 (2.47)	0.82 (3.56)	1.17 (4.38)	0.65 (3.36)	0.66 (3.35)	0.89 (4.24)	1.19 (4.97)	0.53 (3.44)	0.46 (2.91)	0.57 (3.41)	0.74 (3.83)	0.28 (2.36)
Alphas	0.76 (3.52)	1.05 (4.63)	1.39 (5.04)	0.63 (3.12)	0.90 (4.49)	1.13 (5.45)	1.44 (5.99)	0.54 (3.34)	0.72 (4.60)	0.86 (5.30)	1.05 (5.57)	0.33 (2.67)

and others show that momentum profits are correlated with book-to-market ratios. Ang, Hodrick, Xing, and Zhang (2006) show that as idiosyncratic volatility with respect to Fama and French (1993) model increases, the loser momentum portfolio (asymmetrically) generates very low returns. Given this, they argue that one way to increase momentum profits is to short past losers with high idiosyncratic volatility. The regressions we use to measure comovement are based on style returns and not the three-factor model, but our portfolio approach could still simply be a reinvention of the Ang, Hodrick, Xing, and Zhang (2006) results. Although there is little or no theoretical guidance as to why volume could have an important role to play in momentum, several papers show that the connection between volume and future returns is strong and important.[9] Lee and Swaminathan (2000) show that past turnover predicts both the magnitude and duration of price momentum. Their turnover terciles show increasing momentum profits in much the same way as our comovement terciles. Therefore, our results could simply be the volume-return relation in disguise. Although Lee and Swaminathan (2000) do not directly entertain this possibility, it is also entirely feasible that the reverse is true; that is, that their volume return relation simply reflects style investing, not a stock-level momentum life cycle. Regardless of which way the causality runs, we investigate the robustness of our results with respect to trading activity. Also, by construction, comovement is correlated with past returns. We expect and observe this correlation in the data. Among winner stocks ($R10$), the past three-month return of the C1 portfolio is 25.9% and the C3 portfolio is 31.2%. Among loser stocks ($R1$), the past three-month return of the C1 portfolio is -13.6% and the C3 portfolio is -17.8%. The key to our analysis is that comovement generates spreads in momentum returns, over and beyond momentum itself. In other words, as with other spurious variables, we want to ensure that our results are generated by comovement and are not just because we have unwittingly performed a double sort on momentum.

To determine whether any of the above is responsible for the observed differences in returns between comovement terciles, we follow two approaches. First, we follow a triple sort approach as in Ang, Hodrick, Xing, and Zhang (2006). We sort stocks into momentum quintiles and terciles based on the control variable (size, idiosyncratic volatility, etc.) and then, within each of these portfolios, sort stocks into terciles based on comovement. This allows us to examine variation in momentum profits across comovement terciles while controlling for each variable. Although this approach is simple and holds variation within the control variable of interest approximately constant, it has two disadvantages. It does not perfectly isolate the component of comovement that is orthogonal to these variables. More important, it controls for spurious correlations individually, as opposed to jointly, for all variables. Because volume and volatility are themselves correlated, it could be important to control for both of them simultaneously. Therefore, we also use an orthogonalizing regression that addresses both issues. Each month, we regress the style beta on prior values of size, book-to-market ratio, idiosyncratic volatility, turnover, volume, and past six-month returns. We use the residuals from this first-pass regression, which by construction are orthogonal to these characteristics, to sort stocks into comovement terciles (labeled C1* through C3*).

Average monthly returns and alphas from the triple sort approach are shown in Panels A and B of Table 8. There are 18 potential portfolio returns to be displayed for each control variable: two momentum quintiles, times three control variable terciles, times three comovement terciles. To avoid presenting so many numbers, we report collapsed results. We average across the control variable terciles to produce portfolios with dispersion in comovement but with all control variable groups represented.[10]

Our results are not driven by small firms. Controlling for size, the average portfolio returns (alphas) across size terciles shows a difference in C3 and C1 of about 0.43% (0.45%) per month. The C3–C1 return differences are similar for both size tercile 1 and 3. Although not shown in the table, momentum is higher in growth firms. In each comovement tercile, the $R5$–$R1$ returns are higher for low book-to-market firms. But, more important for us, the difference in returns and alphas between low (C1) and high (C3) comovement terciles is present in each book-to-market tercile. Controlling for book-to-market effects leaves a difference in returns between C3 and C1 of 0.39% per month with a t-statistic of 3.24. Controlling for idiosyncratic volatility shrinks the return and alpha differences between C1 and C3. Nonetheless, the monotonicity across comovement terciles remains, with alphas increasing from 0.81% for C1, to 0.86% for C2, to 1.02% for C3. The aggregate difference between C3 and C1 is about 0.21%, large enough to be meaningful, with a t-statistic of 1.94. Controlling for the effects of volume and turnover, comovement continues to generate dispersion in momentum returns. For example, the alpha difference between C1 and C3 controlling for volume is 0.36% with a t-statistic of 3.10 and controlling for turnover is 0.21% with a t-statistic of 2.19. Comovement also explains variation in momentum after controlling for past returns. The return difference between C3 and C1 momentum portfolios is 0.30% per month with a t-statistic of 2.69. Thus our comovement results are not just an artifact of a double sort on past returns.

The upshot of these triple sorts is that although the results survive, for idiosyncratic volatility and turnover,

[9] Two exceptions are Campbell, Grossman, and Wang (1993) and Blume, Easley, and O'Hara (1994). However, both are concerned with short-horizon phenomenon. In the former, volume is an instrument for the demand of liquidity traders that risk-averse market-makers must accommodate; in the latter, volume contains data about the precision of the information about returns (see also Conrad, Niden, and Hameed, 1994). Neither model is designed to predict the sign or the magnitude of the connection between returns and volume.

[10] This approach is identical to that of Table VII in Ang, Hodrick, Xing, and Zhang (2006). A full set of results for each control variable tercile is available upon request.

Table 8
Momentum and comovement based portfolios: controlling for stock characteristics.

The table provides results in Table 6, Panel A for the winner minus loser momentum returns after controlling for stock characteristics. Panels A and B show average monthly returns and alphas for the future six-month returns ($K=6$). We first sort all stocks into momentum quintiles based on the prior six-month return. Then, within each momentum quintile, we further sort stocks into terciles based on the characteristic of interest. Within each of these 15 portfolios, we further sort stocks into comovement terciles. The difference between the long–short momentum spread return for C1, C2, C3, and C3–C1 are shown in the table collapsed across the characteristics portfolios, which shows variation in comovement after controlling for variation in the characteristic of interest. In Panel C, we use component of comovement that is orthogonal to all control characteristics. To do so, we first regress the style beta on size, the book-to-market ratio, idiosyncratic volatility, volume, turnover, and past six-month returns. We use residuals from this regression to sort stocks in comovement terciles C1*, C2*, and C3*. t-statistics are in parentheses.

	C1	C2	C3	C3–C1
Panel A: Average monthly returns with individual controls				
Base results	0.71 (3.67)	0.96 (4.54)	1.15 (4.84)	0.44 (2.98)
Controlling for size	0.47 (3.06)	0.71 (3.86)	0.90 (4.15)	0.43 (3.45)
Controlling for book-to-market	0.51 (3.27)	0.65 (3.61)	0.90 (4.15)	0.39 (3.24)
Controlling for idiosyncratic volatility	0.62 (3.95)	0.68 (3.66)	0.82 (3.95)	0.19 (1.88)
Controlling for volume	0.49 (2.96)	0.71 (3.82)	0.85 (4.15)	0.36 (3.22)
Controlling for turnover	0.61 (3.65)	0.70 (3.71)	0.80 (4.09)	0.19 (2.06)
Controlling for past returns	0.53 (3.24)	0.72 (3.83)	0.83 (4.09)	0.30 (2.69)
Panel B: Fama-French alphas with individual controls				
Base results	0.94 (4.79)	1.19 (5.74)	1.38 (5.79)	0.44 (2.91)
Controlling for size	0.65 (4.29)	0.88 (4.84)	1.10 (4.97)	0.45 (3.38)
Controlling for book-to-market	0.68 (4.42)	0.83 (4.61)	1.10 (4.98)	0.41 (3.27)
Controlling for idiosyncratic volatility	0.81 (5.18)	0.86 (4.72)	1.02 (4.84)	0.21 (1.94)
Controlling for volume	0.68 (4.10)	0.89 (4.82)	1.04 (5.00)	0.36 (3.10)
Controlling for turnover	0.79 (4.65)	0.88 (4.73)	1.00 (5.01)	0.21 (2.19)
Controlling for past returns	0.72 (4.46)	0.91 (4.88)	1.01 (4.85)	0.28 (2.47)
Panel C: Jointly controlling for all characteristics				
Average monthly returns	0.76 (3.55)	0.92 (4.02)	1.16 (4.77)	0.40 (3.05)
Alphas	0.98 (4.53)	1.16 (5.17)	1.41 (5.79)	0.43 (3.21)

the magnitude and statistical significance of the results are diminished. To some extent this is to be expected because both variables are correlated with comovement. But there are reasons to believe that comovement is the driver, not the spuriously correlated, variable. In Barberis and Shleifer (2003), style chasing takes place by supplying and withdrawing capital, thereby generating trading volume (or, equivalently, turnover) and volatility. Thus, in their setup, style investing is the (causal) economic primitive, and volume (or volatility or both) is a correlated outcome. In addition, the fact that our results are generated from both winners and losers, whereas the volatility result of Ang, Hodrick, Xing, and Zhang (2006) comes primarily from losers, suggests that comovement-based results reflect something different from the idiosyncratic volatility puzzle.[11]

Regardless, the triple sorts do not perfectly disentangle the effect of each variable from comovement. Orthogonality is not guaranteed and each correlated variable is dealt with separately. Our second approach, in which portfolios are formed from the residuals of multivariate orthogonal regressions, addresses both these problems. Here the results are more reassuring. Panel C shows that the average monthly return difference between C1* and C3* portfolios is 0.40% with a t-statistic of 3.05. In terms of alphas, the difference is a bit higher: 0.43% with a t-statistic of 3.21. We conclude, therefore, that the ability of comovement to generate variation in momentum returns is not entirely because of its correlation with other variables.

5. Potential explanations

Thus far, we have shown two basic results. First, style returns have some predictive power in the crosssection. Second, the comovement of a stock with its style influences stock-level momentum. These support the case that Barberis and Shleifer (2003) make for style chasing generating stock-level predictability and momentum. But, these could be due to differences in fundamentals. Although we can never irrevocably reject such a hypothesis, we can bring additional evidence to bear on the issue.

5.1. Evaluating risk-based alternatives

Although covariation between comovement portfolios and style returns are necessary for our comovement-based tests, a danger exists that our K period returns could be driven by extremely large portfolio loadings in certain styles. Note that our results are generated not just with raw returns but also with three-factor alphas, thereby controlling for time series variation in the three factors. We report the full time series of loadings of C3 and C1 momentum returns on market, size, and book-to-market factors in Fig. 1. Visual inspection reveals that the loadings of C1 and C3 momentum portfolios on risk

[11] This asymmetry is reflected in the conclusions of Ang, Hodrick, Xing, and Zhang (2006) and is easily seen in their Tables VI and VIII. In the former, the performance of the high-minus-low volatility quintiles is driven entirely by the under-performance of the high volatility quintile instead of the superior performance of the low volatility quintile. In the latter, Ang, Hodrick, Xing, and Zhang (2006) show the same pattern exists while explicitly controlling for momentum.

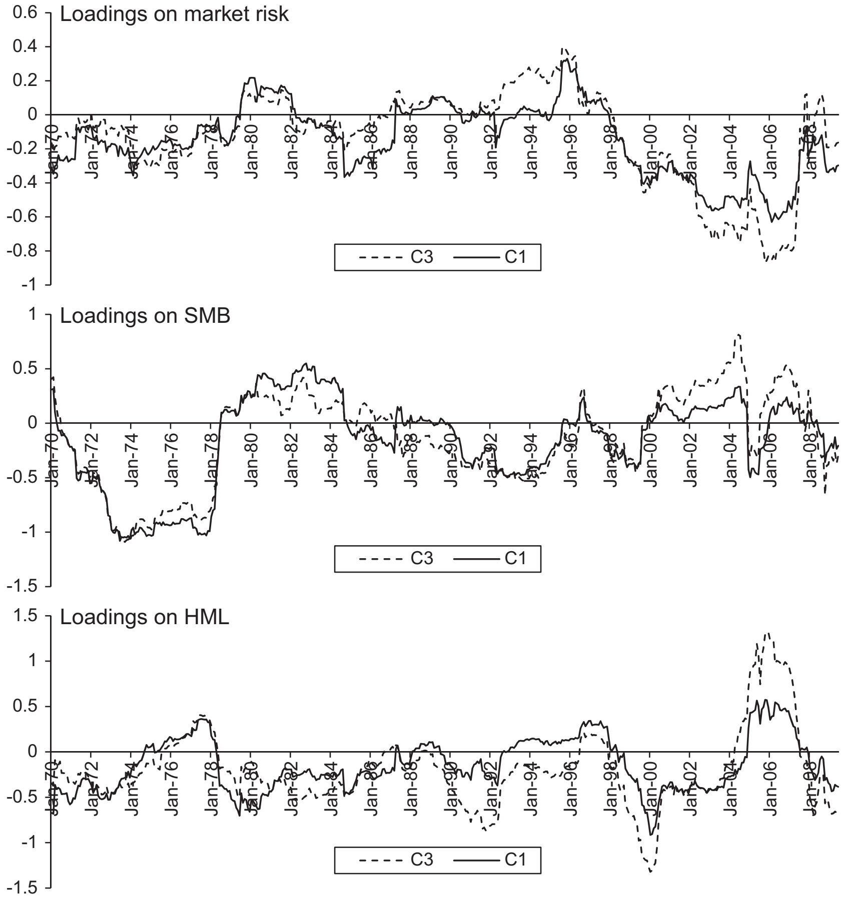

Fig. 1. Loadings on risk factors. The figure shows loadings of C3 and C1 momentum (R10–R1) portfolio returns on the Fama-French three factors [market risk, small minus big (SMB), and high minus low (HML)]in regressions using past 60-month returns and rolling forward one month at a time. Each month, all stocks are sorted into comovement terciles. Then we independently sort stocks into momentum deciles based on their past six-month returns. C3 and C1 portfolios are formed at the intersection of R10 (winner) momentum decile and comovement terciles. The sample consists of all NYSE, Amex, and Nasdaq stocks between 1965 and 2009, excluding stocks in the smallest NYSE size decile and stocks under $5 at the time of portfolio formation, and stocks without valid book-to-market ratios at the end of June of each year. We skip a month between the portfolio formation period and the holding period (six months).

factors are fairly similar over time, suggesting that it is unlikely that known risk factors explain our results.[12]

Notwithstanding the above, we allow for time variation in loadings on risk factors in our portfolios in the following manner. We first run a time series regression of monthly style portfolio returns on the Fama and French risk factors for the entire sample period and record the (unconditional) betas for each style portfolio (generating a matrix of 25×3 betas). Each month, we also calculate the style weights of our comovement–momentum portfolios (i.e., the fraction of each of our portfolios that is invested in each of the 25 style portfolios). These time-varying weights, multiplied by the betas estimated in the first step, generate a time series of loadings on the three risk factors. Multiplying these loadings with factor premiums gives predicted returns. We calculate alphas as the difference between actual returns and predicted returns. With this conditional risk adjustment, the difference between C1 and C3 momentum portfolios is 0.44% per month and has a t-statistic of 3.05. As an additional check, instead of using the entire sample period, we also use rolling five-year windows to calculate betas in the first stage. Here the difference in alpha between the C1 and C3 momentum portfolios is 0.42% per month with a t-statistic of 2.64. These results suggest that time variation in risk does not explain the differences in returns that we find.

Style investing has implications for reversals as well. If style investors move prices away from fundamental value, then reversals should be larger among winner and loser stocks that attracted style investors' interest. In other words, long horizon returns for high comovement terciles should reverse more than low comovement

[12] As with most graphs, it is tempting to look at time periods with which one is familiar and seek validation for priors. For instance, one might look in the 1998–1999 subperiod discussed earlier and see if C3 loads on growth stocks more than C1 (it does). Such visual data mining is useful for looking at time series variation in loadings but also is susceptible to confirmation bias.

terciles.[13] To investigate this, we follow Jegadeesh and Titman (1993) and calculate the average long horizon (event time) returns up to three years after portfolio formation. In our sample, the cumulative return between months 12 and 24 is −2.87% for the C1 momentum portfolio and −4.75% for the C3 momentum portfolio. The difference (1.88%) has a *t*-statistic of 2.45. Over months 13–36, the cumulative returns are −3.69% and −7.36%, respectively, with a *t*-statistic for the difference of 3.34. Thus, not only does comovement generate higher momentum returns during the portfolio evaluation period (K), but it also generates larger reversals in the post-holding period. Jegadeesh and Titman (2001) argue that reversals are inconsistent with the belief that momentum profits are driven by variation in expected returns and suggest that stock-specific overreaction is the culprit. But rational approaches (e.g., growth options) can also deliver reversals. However, neither the stock-specific behavioral explanations nor the rational explanations predict variation in reversals that vary with comovement. The fact that reversals in C3 are larger than in C1 is consistent with style investing.

5.2. *Inferring style effects*

In Barberis and Shleifer (2003), style chasing generates style-level momentum and reversals, which in turn generates similar patterns in asset-level returns. This implies that portfolios formed at the intersection of comovement and asset-level returns should covary with style-level returns. Because loser and winner momentum portfolios are correlated with style returns, this is guaranteed. That is, a mechanical correlation should exisst between style returns and the fraction of a portfolio that is invested in styles that have done poorly or well in the recent past.

This covariation is best illustrated by shifts in performance between value and growth. Consider the period in 1998–1999 when growth stocks performed significantly better than value stocks (see, for example, Chan, Karceski, and Lakonishok, 2000). Barberis and Shleifer (2003) argue that the poor performance of value stocks during this period was because style investors withdrew capital from value stocks to invest in superior performing growth stocks. Because growth stocks are more likely to fall in the R10 and value stocks are more likely to fall in the R1 portfolio, the fraction of our C3 winner portfolio invested in growth stocks over this period should be much higher than the fraction invested in value stocks. To determine whether this is captured by our approach, we calculate the fraction of each portfolio invested in the extreme portfolios of our 5 × 5 size and value-growth grid (i.e., the fraction of the winner and loser portfolios in C1, C2, and C3 invested in the extreme growth or value quintile). In the aforementioned period, the average fraction of the C3 winner portfolio invested in growth stocks was 29%, compared with 16% for value stocks. In fact, such covariation between style returns and our portfolios holds for the entire sample period.[14]

The fact that there is a correlation between past style returns and our portfolios ensures that our results are related to style returns. However, we also try to get a sense of the impact of style investing, first, by trying to measure excess comovement and, second, by measuring the role of style returns on the momentum return difference between C3 and C1. Finally, we show that our results cannot be replicated by randomly assigning stocks into styles. These analyses are inductive in nature and neither approach is foolproof. Therefore, individually we view them as adding to the circumstantial evidence presented above, but collectively they imply that our results are likely to be driven by style investing.

5.2.1. *Extracting nonfundamental comovement*

One way to measure excess (i.e., style investing-based) comovement is to subtract each stock's comovement from its style's long-run average comovement, assuming that the long-run average is approximately equal to the expected comovement of all stocks that belong to that style. However, we cannot use the average beta of all stocks that belong to the same style as a measure of style-level comovement because this average is obviously equal to one when all stocks are included in the calculation of style returns. To measure excess comovement we need a long-run style-level comovement measure that has cross-style variation. The R^2 (of the style beta regression) provides such a measure because the average monthly R^2 of all stocks in a style is not constant across styles and over time. R^2 is also a commonly used measure of comovement (Morck, Yeung, and Yu, 2000; Barberis, Shleifer and Wurgler, 2005). We calculate demeaned R^2 as

$$DR^2_{ist} = R^2_{ist} - \overline{R}^2_s, \tag{2}$$

where $\overline{R}^2_s$ is the long-run average R^2 of all stocks that belong to that style over time. This approach is obviously flawed from a trading strategy perspective because it has a look-ahead bias. However, it can still be informative from an economic viewpoint. The intuition behind it is simply that if the R^2 of a stock with respect to a style is much higher than the time series mean $\overline{R}^2_s$ of the style, it is likely to be caused by style investing.

The returns and alphas for comovement terciles based on this demeaned R^2 measure are shown in Panel A of Table 9. For the J, K=6 formation and evaluation horizons, the return

[13] This is most starkly seen in the asset-level impulse responses that Barberis and Shleifer (2003) use to illustrate their model (see Fig. 2 in their paper).

[14] To check that such covariation exists in the entire sample, we calculate relative style return differences and correlate them with differences in the fraction of each portfolio devoted to value versus growth and small versus big firms. For example, we compute the difference in returns between the highest and lowest book-to-market quintile over the previous three months. We then calculate the difference in the fraction of the C3 winner and loser portfolios devoted to value versus growth firms. The correlation between these returns and portfolio weight differences is 0.56 for winners and −0.54 for losers—the winner C3 portfolio loads positively on value firms when value firms have higher returns than growth firms, and symmetrically, the loser C3 portfolio loads negatively on value firms when value firms have lower returns than growth firms. Similar such covariation is observable for small versus big firms.

Table 9
Comovement terciles constructed from demeaned R^2 and style returns.

In Panel A, we first calculate demeaned R^2 as the deviation of a stock's R^2 from the long run average R^2 of all stocks that belong to its style. Comovement terciles are formed based on this demeaned R^2. The panel shows equal-weighted monthly momentum returns and alphas for the given horizons. In Panels B and C, comovement terciles are formed based on β_{is}, as before. However, returns to the portfolios are based on the style component of returns, computed as the product of β_{is} and the style return (R_{st}). Panel B shows alphas for each comovement tercile based on the three-factor model. Panel C shows the alpha differences between C1 and C3 based on total returns, style returns, and the percentage of the former explained by the latter. t-statistics appear in parentheses.

	Holding period: 3 (K=3)				Holding period: 6 (K=6)				Holding period: 12 (K=12)			
	C1	C2	C3	C3–C1	C1	C2	C3	C3–C1	C1	C2	C3	C3–C1
Panel A: Comovement measured using demeaned R^2 with portfolios formed over six months (J = 6)												
Returns	0.54 (2.34)	1.09 (4.41)	1.06 (3.90)	0.52 (3.22)	0.65 (3.04)	1.05 (4.73)	1.16 (4.77)	0.51 (3.78)	0.41 (2.37)	0.65 (3.65)	0.75 (3.74)	0.34 (3.07)
Alphas	0.78 (3.45)	1.30 (5.30)	1.26 (4.56)	0.48 (2.95)	0.89 (4.24)	1.29 (5.90)	1.39 (5.55)	0.50 (3.62)	0.68 (4.11)	0.93 (5.43)	1.04 (5.29)	0.36 (3.26)
*Panel B: Alphas based on the style component of returns (β_{is} * R_{st}) with J=6*												
Alphas	−0.06 (−0.48)	0.08 (0.66)	0.19 (1.39)	0.25 (3.14)	−0.09 (−0.84)	0.06 (0.63)	0.16 (1.31)	0.24 (3.98)	−0.10 (−1.25)	0.01 (0.11)	0.04 (0.47)	0.14 (2.96)
Panel C: Percentage of alpha differences between C1 and C3 explained by style component of returns												
Total returns		0.48				0.50				0.36		
Style returns		0.25				0.24				0.14		
Percentage explained		52				48				39		

and alpha differences between C1 and C3 are 0.51% and 0.50% per month, respectively, and both are statistically significant.

5.2.2. *A return decomposition*

We also try to get a sense of the impact of style investing on return predictability using the style betas in Eq. (1). Instead of using total stock returns to generate portfolio returns for C1 and C3, we multiply the style beta (β_{is}) with the style return to get at the style component of the total return. We then use this style component in all our portfolio analysis. Effectively, we are inferring the contribution of style investing on asset-level return predictability. Barberis and Shleifer (2003) argue that this contribution should be positive but likely less than 100%, allowing a role for security-specific noise trading effects.

We present the results in Panel B of Table 9. Because the style component includes exposures to size and book-to-market factors (by construction), we report only three-factor alphas. The results continue to show differences in alphas between C1 and C3. For J, K= 6, the return difference is 0.24% per month with a t-statistic of 3.98. Panel C shows that approximately 50% of the difference in alphas between C1 and C3 is attributable to the style component of returns. This is consistent with the Fama-MacBeth regressions reported in Table 1.

5.2.3. *Random styles*

All of our results are tests of the joint hypothesis that style investing affects stock return predictability and that we correctly identify styles. In other words, if we cannot do a good job in identifying styles that investors follow, we should not find any differences between comovement terciles. However, if the results are driven by some mechanical reason (such as how stocks are sorted into comovement portfolios), then regardless of our way of identifying styles the results should continue to hold.

To test this possibility we allocate stocks randomly into 25 portfolios and repeat all of our tests. We do not find any difference of momentum returns between C3 and C1. For J=6 and K=6 the difference of momentum returns between C3 and C1 is 0.00011 with a t-statistics of 0.09. This suggests that our results are not an artifact of mechanical effects but instead are driven by style investing.

6. Conclusion

Style investing is ubiquitous. As retail investors have reduced the fraction of directly held equity, they have concomitantly increased their holdings of mutual funds, almost all of which are classified based on investment styles. Similarly, the vast majority of plan sponsor (institutional) allocations to equity are also based on investment styles (see, for example, Goyal and Wahal, 2008). In retail as well as institutional arenas, investors, investment advisers, and plan fiduciaries use size and value-growth metrics in comparing investment alternatives. Yet, with the exception of the studies cited in the introduction, academic attention on the impact of style investing on asset prices does not appear to be commensurate with its apparent importance to investors.

In this paper, we investigate the role of style-based investing on asset-level return predictability. Our motivation for this undertaking is the remarkably simple prediction provided by Barberis and Shleifer (2003), namely, that under certain conditions, style investing can generate predictability in returns. Consistent with this, the profits of winner, loser, and long–short momentum portfolios are directly related to the comovement of a stock with its style. Fama-MacBeth regressions also indicate that past style returns have some predictive power over and beyond stock's own past return. As we have recognized above, we cannot conclude that rational or stock-specific behavioral biases are not responsible for predictability in returns. We can, however, conclude that investing behavior in which investors chase style returns amplifies the waves in asset returns.

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