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On Characteristics Momentum

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This article investigates whether investors can benefit from information about equity style evolution. The study shows that portfolios formed by firm characteristics such as size, book-to-market, and/or dividend yield can be used to determine investment style dominance. Characteristics momentum, buying stocks with persistent in-favor characteristics and selling stocks with persistent out-of-favor characteristics, conveys valuable information about future stock returns. It is distinct and has longer-lasting effects than price or industry momentum in predicting future returns. In explaining the existence of characteristics momentum profits, this study highlights the importance of slow evolution of changes in firm characteristics. The lifecycle of investment styles can thus have predictive power for trend-chasing investors, who can potentially push up the price of stocks with an in-favor style, and depress the price of stocks with an out-of-favor style.

It is well known in the investment industry that the single largest determinant of active equity management performance is not specific security selection, but style emphasis. Typically, style emphasis explains more than 90% of the total variation of a manager's performance. For example, Sharpe [1992] shows that about 97% of Fidelity Magellan Fund's[1] superior performance over the 1980s is attributable to correct investment style allocation, not superior stock-picking.

The focus on investment styles is particularly attractive to such institutional investors as pension funds and endowments, because it enables them to organize and simplify their portfolio allocation decisions, as well as measure and evaluate the performance of professional managers relative to specified style benchmarks. Individual investment styles perform differently during various stages of a market cycle. For example, small-cap stocks outperformed large-cap stocks in the 1970s, but large-caps outperformed small-caps in the 1980s. Growth stocks outperformed value stocks in 1998 while the opposite occurred in 1997. No single style or mix of styles is definitively optimal over all periods. But recognizing that, over time, outperformance and underperformance of styles will eventually balance, there may be opportunities to enhance profits.[2] That is, if one can identify the style cycle currently in favor, selecting a money manager representing that style may maximize profits.[3] Profitable trading strategies may especially exist if an investment style becomes popular for a long time.

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The practice of chasing an in-favor investment style is not uncommon in the investment industry. In an investment tournament, in which money managers compete for fund inflows and ultimately for compensation, managers have an incentive to game the investment style to improve relative ex post performance rankings. In fact, the financial press has identified several such cases (for examples, see Tam [2000] and Egodigwe and O'Brian [2000]).

This study examines the important issue of whether rotation among different investment styles provides opportunities for portfolio performance enhancement. Although several studies[4] have documented that professional active money managers have neither market timing nor style timing ability, this study first empirically addresses the more passive question of whether (professional) investors can profits from chasing current in-favor investment styles.[5]

This study first proposes eighteen style portfolios formed by firm characteristics size, book-to-market, and dividend yield to represent investment styles. After showing that these style portfolios can be used to determine style dominance, several possible characteristics momentum trading strategies are explored for a stringent check on whether style cycle information can enhance returns. This paper confirms that drifts in future returns over the next twelve months are predictable from equity style cycle information. In other words, stocks with in-favor characteristics continuously outperform stocks with out-of-favor characteristics.

However, one may argue that the characteristics momentum examined here could be just a miracle of price momentum (Jegadeesh and Titman [1993]) or industry momentum (Moskowitz and Grinblatt [1999]) documented in the literature, since past winners (losers) or stocks from past winning (losing) industries would most likely be the stocks with consistent in-favor (out-of-favor) firm characteristics in the past. To remove any confounding effects associated with price and industry momentum, we perform analyses on the basis of independent two-way classifications and Fama and MacBeth [1973] cross-sectional regressions at each point in time on the universe of securities. This study shows that characteristics momentum has independent explanatory power for future returns and is distinct from price and industry momentum.

Furthermore, characteristics momentum has longer-lasting effects in predicting future returns than price or industry momentum. However, the existence of such characteristics momentum profits is attributable to dynamics of firm characteristics that do not change greatly over a short horizon. As a result, trend-chasing investors can confidently allocate more resources to styles with strong prior records and further inflate the price of stocks with an in-favor style. At the same time, trend-chasing investors can finance a shift into successful styles by withdrawing resources from poorer-performing ones, and further depress the price of stocks with out-of-favor styles.

The rest of the paper is organized as follows. The first section constructs eighteen style portfolios and examines whether they can be used to determine investment style dominance. The second section evaluates characteristics momentum strategies, while the third section shows distinct characteristics momentum. The fourth section conducts the performance frequency comparison between static and momentum investment strategies. The fifth section discusses possible causes for the profitability of characteristics momentum strategies. The final section summarizes our conclusions.

Style Portfolios

Attributes of the Eighteen ME-BM-DY Sorted Portfolios

Kothari and Shanken [1997] find reliable evidence that both book-to-market and dividend yield track time series variation in expected real stock returns over the period 1926–1991. After examining factors formed by several fundamental variables, Chan, Karceski, and Lakonishok [1998] conclude that size, book-to-market, and dividend yield are the most important fundamental factors. Therefore, portfolios formed by these dimensions are proposed here. For a robustness check, however, portfolios formed only by size and book-to-market are also performed. The portfolio formation is done at the beginning of each month, and the value-weighted returns are calculated for each portfolio for the month. The details are as follows.

All NYSE stocks are first ranked by their market capitalization (ME), book-to-market (BM), and dividend yield (DY)[6] independently at the beginning of each month from July 1963 through December 1997. All NYSE, AMEX, and Nasdaq stocks are then independently allocated to three ME and three BM groups (low, medium, or high) based on the contemporaneous breakpoints for the bottom 30%, the middle 30%, and the top 40%[7] of the values of ME and BM for NYSE stocks. NYSE, AMEX, and Nasdaq stocks are allocated in an independent sort to two groups based on whether their DY is below or above the contemporaneous median DY for NYSE stocks.

To reduce confounding factors due to marketwide movements, stocks were compared to the contemporaneous NYSE breakpoints rather than to the previous NYSE breakpoints.[8] Eighteen ME-BM-DY portfolios are defined as the intersections of the three ME, three BM, and two DY groups. The firms remain in these portfolios for the month. Therefore, time series monthly returns of each portfolio are built up and used to determine in-favor and out-of-favor investment styles to perform the characteristics momentum strategy.

The procedure is repeated every month to make characteristics identification fresh and to allow characteristics to vary over time. Berk, Green, and Naik [1999] argue that during each period cash flows from existing assets may die off, and new investment opportunities are presented to firms. Changes in systematic risk follow from dynamic value-maximizing choices by firms. At the same time, firm characteristics, serving as state variables that summarize the systematic risk of existing assets and the relative importance of growth opportunities, also change. As a result, it is necessary to frequently update portfolios formed by varying firm characteristics to capture the dynamics of the firm's systematic risk,[9] and to confirm the most current in-favor and out-of-favor investment styles.

Table 1 shows the mean statistics for the eighteen size/book-to-market/dividend-yield sorted portfolios over the period July 1963 to December 1997. These portfolios are based on unconditional sorts using NYSE breakpoints. For example, the small/growth/low-DY portfolio is the set of firms included on NYSE/AMEX or Nasdaq that have market equity in the range of the lowest thirtieth percentile of NYSE firms, book-to-market ratios in the lowest thirtieth percentile of NYSE firms, and dividend yield in the bottom half of NYSE firms. All portfolios are rebalanced monthly.

Panel A illustrates the magnitude of the return differential across portfolios. First, given the same size and dividend yield, the difference in returns of high book-to-market stocks over low book-to-market stocks ranges from 31 to 49 basis points per month over this period. Across the size dimension, the mean return of small firms over large firms ranges from 9 to 29 basis points per month, and the difference is much smaller in growth firms with low dividend yield.

Table 1. *Statistics of Size, Book-to-Market, and Dividend Yield Sorted Portfolios by the Characteristics Partition Approach (July 1963–December 1997)*

	Growth		← Book-to-Market →		Value	
	Low-DY	**High-DY**	**Low-DY**	**High-DY**	**Low-DY**	**High-DY**
Panel A: Mean of Monthly Value-Weighted Returns (%)						
Small	1.054	1.239	1.227	1.291	1.544	1.624
↑	(7.30)	(5.41)	(6.57)	(4.60)	(6.73)	(5.08)
Size	1.144	1.130	1.154	1.092	1.557	1.537
↓	(6.44)	(4.72)	(5.98)	(4.26)	(6.62)	(4.67)
Large	0.967	0.951	0.972	1.039	1.273	1.382
	(5.09)	(4.27)	(5.17)	(4.02)	(6.05)	(4.40)
Panel B: Systematic Risk—Value-Weighted Beta						
Small	1.453	0.948	1.360	0.861	1.311	0.960
↑	[1.20]	[0.84]	[1.08]	[0.79]	[1.07]	[0.80]
Size	1.413	0.973	1.332	0.882	1.391	0.970
↓	[0.97]	[0.69]	[0.95]	[0.69]	[0.86]	[0.73]
Large	1.128	0.904	1.210	0.859	1.286	0.916
	[0.77]	[0.54]	[0.80]	[0.63]	[0.79]	[0.64]
Panel C: Turnover of Trading Volume (10^{-4})						
Small	38.72	29.72	26.03	14.85	23.56	12.98
Size	41.71	18.21	30.36	13.32	29.82	15.43
Large	30.62	15.02	27.38	15.51	27.83	17.96
Panel D: Changes in Portfolio Composition (%)						
Small	9.83	21.64	26.78	23.87	10.77	10.37
Size	14.13	23.94	28.89	21.16	21.20	14.26
Large	9.74	16.27	24.50	16.21	21.42	11.90
Panel E: Industry Representation						
Small	18.38	11.09	18.31	15.66	19.12	19.08
↑	[200.62]	[10.97]	[89.48]	[25.15]	[158.93]	[82.19]
Size	17.42	10.86	16.50	15.99	14.89	18.14
↓	[56.16]	[8.01]	[17.25]	[26.33]	[12.84]	[39.29]
Large	17.55	13.51	15.02	17.13	10.64	16.73
	[40.46]	[14.79]	[9.71]	[36.27]	[5.32]	[31.36]
Panel F: Mean of Number of Stocks						
Small	756.34	37.57	393.89	106.06	784.40	342.42
Size	212.94	31.29	79.98	92.69	53.27	125.66
Large	178.23	63.12	48.78	117.67	22.28	108.07
Panel G: Mean of Value Proportion (%)						
Small	1.68	0.11	0.79	0.37	0.95	0.90
Size	3.17	0.48	1.16	1.47	0.74	1.98
Large	30.13	15.21	5.69	19.21	1.80	14.16
Panel H: Mean of Number Proportion (%)						
Small	19.02	0.97	10.40	3.05	19.96	10.24
Size	6.01	0.84	2.41	2.73	1.61	4.20
Large	6.38	1.85	1.96	3.90	0.79	3.68

Note: All NYSE stocks are first ranked by their market capitalization (ME), book-to-market (BM), and dividend yield (DY) at the beginning of each month from July 1963 through December 1997. All NYSE, AMEX, and Nasdaq stocks are then independently allocated to three ME and BM groups (low, medium, or high) based on the contemporaneous breakpoints for the bottom 30%, middle 30%, and top 40% of the values of ME and BM for NYSE stocks. NYSE, AMEX, and Nasdaq stocks are allocated in an independent sort to two groups based on whether their DY is below or above the contemporaneous median DY for NYSE stocks. Eighteen ME-BM-DY portfolios are defined as the intersections of the three ME, three BM, and two DY groups. The firms remain in these portfolios for the entire month.

Panel A shows the average of the monthly value-weighted returns for each portfolio; the time series standard deviation is shown in parentheses. Panel B shows the time series average of the value-weighted systematic risks for each portfolio. The systematic risk of a stock is the coefficient estimated from the regression of the stock's monthly excess returns on the monthly excess returns of the value-weighted market portfolio over the prior three-year interval. This analysis is performed at the end of every year. The ratio of the standard deviation of systematic risks across stocks in a particular portfolio over that across stocks in the universe is computed, and the time series average of the ratios is reported in brackets in Panel B. Panel C reports the average daily turnover of trading volume over the prior six-month interval. The ratio is the daily volume divided by the number of shares outstanding and is calculated each June and December. Panel D reports the time series average of changes in portfolio composition. It reports the maximum number proportion of stocks that move in and out of a given portfolio every month. These number proportions are calculated each June and December. Panel E reports the number of distinct industries, and the maximum number of firms in a particular industry within a cell is shown in brackets. Panel F shows the average of the monthly number of stocks in each portfolio. In Panel G, the total value of each portfolio is expressed as a percentage of market capitalization of all eligible stocks. Panel H expresses a percentage of number of stocks for each portfolio. The table reports the percentage averaged across all months in Panels G and H.

Along the dividend yield dimension, small firms with high dividend yield outperform small firms with low dividend yield by 8 to 19 basis points. Although the returns here are almost monotonic in size, they are not so in either book-to-market or dividend yield. Therefore, a simple linear or log-linear regression of returns on capitalization, book-to-market ratios, and dividend yield will not adequately characterize observed stock returns.

According to Berk, Green, and Naik [1999], firms with the same characteristics tend to have the same state variables that determine their systematic risks and expected returns. It is expected that the cross-sectional standard deviation (s.d.) of systematic risks across all stocks in a style portfolio is less than the s.d. of systematic risks across the whole universe of stocks.[10] Otherwise, it may indicate that the proposed style portfolios cannot capture the underlying pervasive forces affecting asset returns.

Panel B of Table 1 shows the time series average of value-weighted annual betas for each portfolio, and reports the ratio of the s.d. of systematic risk across all stocks within a portfolio over the s.d. across the whole universe of stocks. The systematic risk of a stock is the coefficient estimated from the regression of the stock's monthly excess returns on the monthly excess returns of the value-weighted market portfolio over the prior three-year interval. All portfolios, except for small stocks with low dividend yield, have a ratio lower than 1. Notably, low-dividend yield firms and high-dividend yield firms persistently generate quite different risk attributes here, even though the difference in both returns is small, as Panel A shows. This implies that the dividend yield cannot be ignored in the analysis.

Panel C reports the average daily turnover of trading volume over the prior six-month interval. The turnover is defined by the daily share traded divided by the number of shares outstanding. On average, stocks with low dividend yield are traded more often. Panel D shows the persistence of portfolio characteristics by reporting the time series average of changes in portfolio composition.[11] Growth stocks with low dividend yield and value stocks with high dividend yield tend to persist in their characteristics so that changes in the portfolio composition of these stocks are relatively low.

In response to industry momentum strategies recently documented by Moskowitz and Grinblatt [1999], at the end of each month we classify a firm into one of twenty industries by using their two-digit SIC code. Panel E shows the time series average of the number of distinct industries. The time series average of the maximum number of firms in a particular industry within a style portfolio is shown in brackets. As the numbers show, most firms in a cell are not concentrated in a particular industry.

For example, there are about nineteen distinct industries in the portfolio where firms have small value with low dividend yield, and the maximum number of firms in one of these nineteen industries is about 159, out of 784 shown in Panel F. Although only about eleven of twenty industries are present in the portfolio of large value stocks with low dividend yield, this portfolio has the fewest stocks shown in Panel F.

Panels F to H show the average sample size and the value and number proportion of each style portfolio. The minimum sample size, 22.28, is in the portfolio comprising large value stocks with low dividend yield. Although small-cap stocks with low dividend yield account for 49.38% of the universe of stocks, they account for only 3.42% in terms of total value.

Investment Style Dominance

According to Berk, Green, and Naik [1999], firms with the same characteristics tend to have the same state variables that determine their systematic risks and expected returns. This implies that the style portfolios formed by firm characteristics can price individual stocks, since such characteristics represent underlying forces affecting asset returns.

Fama and French (FF) [1996] argue that many CAPM average return anomalies are captured by three factors - market, size, and book-to-market. We therefore use their three-factor model as the comparison benchmark[12] to test whether the proposed style portfolios can determine style dominance. In other words, can they price stock returns more precisely and produce less dispersed forecast errors? We perform the test on an individual stock and out-of-sample basis. We believe this will ensure the full utilization of information about the cross-sectional behavior of individual stocks, and be less likely to produce such spurious results as Lo and MacKinlay [1990] and Roll [1977] have noted.

The FF three-factor regressions are estimated for each stock for each month beginning in June 1968, using a rolling window of five years of past monthly returns.[13] We use the in-sample regression coefficients and the values of the explanatory variables for the nth month ahead following the in-sample period to make out-of-sample forecasts of stock returns.

In the proposed style portfolios formed by firm characteristics (hereafter SPC), we use observable characteristics to assign each stock to one of the $3 \times 3 \times 2$ portfolios for each month, also beginning June 1968. A stock's return forecast for the nth month ahead is simply the value-weighted return of the assigned style portfolio in the nth month ahead, while the stock is assigned to the portfolio today according to its current characteristics. Note that the stock may not be in the same assigned style portfolio n month(s) ahead. We measure the forecast power by the absolute deviation of the forecasted return from the realized return.

Table 2 includes securities existing at least five years prior to a testing month. In describing a stock's expected

Table 2. *Absolute Return Prediction Errors*

	Forecast Horizon					
	1 month	6 months	1 year	2 years	3 years	5 years
SPC (3 × 3 × 2)	7.530	7.565	7.588	7.610	7.594	7.645
FF	7.798	7.833	7.870	7.871	7.856	7.893
Diff.	–0.267	–0.270	–0.287	–0.266	–0.278	–0.264
	(–13.17)	(–12.84)	(–13.29)	(–13.38)	(–13.95)	(–13.49)
SPC (5 × 5)	7.529	7.578	7.599	7.628	7.601	7.631
FF	7.794	7.830	7.866	7.866	7.849	7.893
Diff.	–0.265	–0.256	–0.275	–0.250	–0.264	–0.247
	(–12.93)	(–12.18)	(–12.60)	(–12.26)	(–13.06)	(–12.30)

Note: Given a firm's characteristics (size, book-to-market, and dividend yield) observed at the beginning of each month, the stock is assigned to a 3 × 3 × 2 style portfolio. The stock's return forecast based on the style portfolios formed by characteristics (SPC) for month $t + i$ is the return of the assigned portfolio in month $t + i$. The regression forecasts for month $t + i$ (I = 1, 6, 12, 24, 36, 60) combine slopes estimated from the prior five–year interval and explanatory returns for month $t + i$. The prediction error is defined by subtracting the expected return from the realized return. The one-month-ahead results summarize monthly forecast errors for July 1968 through December 1997. The one-year-ahead results summarize monthly forecast errors for June 1969 through December 1997, and the five–year–ahead results are for June 1973 through December 1997. The absolute value of prediction errors is calculated for each stock, and the time series cross-sectional average of absolute prediction errors is reported. For a robustness check, we also construct 5 × 5 style portfolios based on the quintile breakpoints of size and book-to-market of NYSE firms in a similar manner. The average differences in absolute prediction error between the characteristics partition approach and the Fama and French model (SPC – FF) are reported in the "Diff." row, and the associated t–statistics are reported in parentheses.
Fama and French (FF) regressions: $R_i - R_f = a_i + b_i(R_M - R_f) + siSMB + h_iHML + \varepsilon_i$

return, the SPC focuses on three firm characteristics and allows eighteen degrees of freedom, while the FF focuses on three factors and allows non-limited degrees of freedom via continuous factor loadings. It is therefore quite striking that the 3 × 3 × 2 partition predicts future returns better than the FF three-factor model.

On average, the SPC produces an absolute error of 7.53% in the one-month-ahead forecast and 7.645% in the sixtieth-month-ahead forecast, while the FF produces errors of 7.798% and 7.893%, respectively. This result is statistically significant and does not depend on whether the forecast error is equally weighted or value-weighted. In an analysis of the style and performance of mutual funds, Chan, Chen, and Lakonishok [2002] also document that the holdings-based approach, similar to our characteristics partition approach here, generally gives closer predictions of funds' future performance than the FF model.

However, this comparison may not be adequate, because our characteristics partition approach considers three characteristics dimensions—size, book-to-market, and dividend yield. The FF model considers only the first two. Therefore, we construct a 5 × 5 ME-BM partition[14] in a similar manner and repeat the same test. The SPC result is still more favorable, which is again surprising. Note that the prediction power of the 3 × 3 × 2 partition is no worse than that of the 5 × 5 partition, even though the former has fewer portfolios. This result promises interesting future research on the relationship between the partition dimensions and the partition numbers.

We further explore whether the 3 × 3 × 2 partitions continue to produce smaller prediction errors than the FF model in small stocks with low dividend yield that have high beta dispersion within the portfolio shown in Panel B of Table 1. The SPC again is significantly better at predicting future returns in both groups, small stocks with low dividend and the others.[15]

In summary, firm characteristics represent the underlying pervasive forces affecting asset returns, and the style portfolios formed by such characteristics can thus be used to identify the current in-favor and out-of-favor equity styles.[16] Whether institutional and individual investors can benefit from style cycle information by performing characteristics momentum strategies is examined next.

Characteristics Momentum

Momentum Strategies

If equity style cycles are of long duration, it might be easier to make profitable trading strategies that select stocks with consistently in-favor or out-of-favor characteristics in the past. We explore several possible trading strategies for a stringent check on whether such opportunities exist. The strategies select stocks based on the returns of their assigned style portfolios over the past one, two, three, or four quarters. We also consider holding periods that vary from one to four quarters over the next year, and post-holding periods of the second and third year following portfolio formation. This gives a total of twenty-four strategies.

Jegadeesh and Titman [1993] note that including portfolios with overlapping holding periods in the examined strategies can improve the power of the tests. Therefore, in any given month t, the strategies hold a series of portfolios selected in the current month as well as in the previous $K - 1$ months, where K is the holding period.

Specifically, a strategy that selects stocks in a style portfolio on the basis of returns over the past J months and holds them for K months is constructed as follows. At the beginning of each month t, the eighteen style portfolios are ranked in ascending order on the basis of their compounded returns in the past J months. Based on these rankings, the top two are called in-favor style portfolios, and the bottom two are called out-of-favor style portfolios. In each month t, the strategy buys stocks from the in-favor style portfolios and sells them from the out-of-favor style portfolios and holds this position for K months. As a result, the compositions of the winner or loser portfolio are unchanged during the K months following the portfolio formation. The strategy closes out the position initiated in month $t - K$. The profits from these strategies are calculated for a series of portfolios balanced monthly to maintain equal weights.

Table 3 reports the average returns of the different buy-and-sell portfolios as well as the zero-cost, buy-minus-sell portfolio. The returns of all the zero-cost portfolios are positive. Since portfolio returns are measured over overlapping holding periods, the t-statistics are corrected for serial correlation and heteroskedasticity. All returns are statistically significant at a 5% level. The most successful zero-cost strategy selects stocks based on their characteristics trend over the previous twelve

Table 3. Returns of Characteristics Momentum Strategies

	Holding Months					
J K =	**3**	**6**	**9**	**12**	**2nd Year**	**3rd Year**
			Panel A: No Gap			
3 Buy	1.527	1.405	1.394	1.440	1.252	1.332
3 Sell	0.939	1.030	1.015	0.957	1.195	1.226
3 Buy-Sell	0.588	0.374	0.378	0.483	0.058	0.106
	(3.32)	(2.32)	(2.60)	(3.92)	(0.52)	(0.74)
6 Buy	1.493	1.466	1.492	1.456	1.297	1.363
6 Sell	1.090	1.053	0.992	0.995	1.172	1.193
6 Buy-Sell	0.403	0.412	0.500	0.462	0.125	0.170
	(2.22)	(2.42)	(3.36)	(3.38)	(0.87)	(1.04)
9 Buy	1.579	1.536	1.492	1.467	1.312	1.382
9 Sell	1.026	0.968	0.962	0.962	1.121	1.171
9 Buy-Sell	0.554	0.568	0.531	0.505	0.191	0.211
	(3.02)	(3.43)	(3.52)	(3.55)	(1.19)	(1.34)
12 Buy	1.606	1.516	1.516	1.482	1.317	1.411
12 Sell	0.824	0.859	0.866	0.890	1.062	1.213
12 Buy-Sell	0.782	0.657	0.650	0.592	0.255	0.198
	(4.29)	(3.97)	(4.18)	(3.88)	(1.40)	(1.21)
			Panel B: Month Skipped			
3 Buy	1.384	1.331	1.386	1.387	1.257	1.308
3 Sell	1.042	1.099	1.020	1.002	1.192	1.234
3 Buy-Sell	0.342	0.232	0.366	0.385	0.065	0.074
	(1.89)	(1.45)	(2.61)	(3.18)	(0.62)	(0.52)
6 Buy	1.419	1.448	1.460	1.413	1.310	1.381
6 Sell	1.166	1.070	1.008	1.019	1.188	1.186
6 Buy-Sell	0.253	0.378	0.452	0.395	0.122	0.195
	(1.37)	(2.31)	(3.06)	(2.96)	(0.83)	(1.24)
9 Buy	1.515	1.509	1.473	1.433	1.321	1.390
9 Sell	0.989	0.977	0.963	0.971	1.115	1.186
9 Buy-Sell	0.526	0.532	0.510	0.462	0.206	0.204
	(2.96)	(3.25)	(3.40)	(3.24)	(1.27)	(1.33)
12 Buy	1.517	1.507	1.491	1.446	1.323	1.392
12 Sell	0.915	0.909	0.910	0.927	1.049	1.228
12 Buy-Sell	0.602	0.598	0.581	0.519	0.274	0.164
	(3.21)	(3.53)	(3.65)	(3.27)	(1.50)	(1.04)

Note: At the beginning of every month from July 1964 through December 1997, eighteen ME-BM-DY sorted portfolios are first ranked by their prior J-month compounded returns. The stocks in the top two ranking portfolios form a "buy" portfolio, while stocks in the bottom two ranking portfolios form a "sell" portfolio. Both "buy" and "sell" portfolios are held for K subsequent months. The values of J and K for the different strategies are indicated in the first column and row, respectively. All stocks are equally weighted in the portfolios. The average monthly returns of these portfolios are shown in a percentage format. The t-statistics with the Newey-West estimators adjusted for standard errors are reported in parentheses. Panel A reports the profits when no gap exists between the portfolio formation period and the holding period; Panel B skips a month between the portfolio formation and holding periods.

months and then holds the portfolio for three months. This strategy yields 0.782% per month.

In their price momentum strategy, Jegadeesh and Titman [1993] also find that this strategy is the most profitable. However, the characteristics momentum profits over the post-holding periods of the second and third years after portfolio formation are not significant. Jegadeesh and Titman [2001] also find no evidence of significant return reversals over the same post-holding periods in their price momentum strategies.

From a practical investment perspective, we need to account for transaction costs to assess whether the characteristics momentum strategies are still profitable. The characteristics momentum strategy that ranks on six months and holds for six months requires an average turnover of 84.3% semiannually.[17] Break-even transaction costs are therefore approximately 73 basis points per dollar of one-way long or short transactions. Table 3 shows that holding such a momentum strategy for an additional six months beyond the initial six-month holding period does not reduce the average monthly return. Thus, it is likely to reduce turnover to 85% per year, raising the break-even transaction cost to 163 basis points per dollar of one-way long or short transactions. Berkowitz, Logue, and Noser [1988] estimate one-way transaction costs of 23 basis points for institutional investors. Chan and Lakonishok [1995] report average trading costs for small firms of about 150 basis points per trade. Therefore, the 163-basis point break-even transaction cost appears to far exceed the actual transaction costs if characteristics momentum does not cluster in small-cap stocks only over time. We examine this issue in the next section.

Lo and MacKinlay [1990] and Jegadeesh and Titman [1995] show that stock portfolios can exhibit positive serial correlation due to lead-lag effects associated with firm size. Jegadeesh [1990] documents the effect of the bid-ask spread on return calculation. To mitigate such confounding effects on the characteristics momentum portfolios, we skip a month between the ranking period and the holding period in Panel B of Table 3. As expected, when the portfolios are formed by prior three- or six-month returns, the confounding effects show up most strongly in the month closest to portfolio formation. Other numbers come out very closely to those in Panel A of Table 3. The overall results in Table 3 are consistent with Jegadeesh and Titman [1993, 2001] for individual stock returns, and with Moskowitz and Grinblatt [1999] for industry returns, where momentum profits are strong over intermediate holding periods (three to twelve months), but diminish beyond a year.

For a robustness check, we also perform characteristics momentum strategies based on the twenty-five partitions formed by quintile size and book-to-market in a similar construction of the eighteen ME-BM-DY sorted style portfolios. The result is similar. For example, the most successful zero-cost strategy ($J = 12$, $K = 3$), which selects stocks based on returns to their assigned style portfolios over the previous twelve months and then holds the portfolio for three months, yields 0.928% per month. The least profitable zero-cost strategy ($J = 3$, $K = 6$) yields 0.307% per month. All returns of zero-cost portfolios over holding periods are statistically significant at a 5% level. Chen and De Bondt [2002] also document that such a zero-cost strategy ($J = 12$, $K = 3$) works within S&P 500 stocks and yields 0.475% per month significantly.

Distribution of In-Favor and Out-of-Favor Characteristics

In this section we examine whether characteristics momentum clusters in a few stocks with certain characteristics. Characteristics are in-favor if the portfolios formed by them have high prior returns; characteristics are out-of-favor if the portfolios have low prior returns. Table 4 reports the percentage frequency of characteristics appearing in- or out-of-favor over the entire sample period from July 1964 to December 1997.

When in-favor characteristics are defined by the prior three-month returns of characteristics sorted portfolios, there is a tendency for investors to initially favor both small-caps and large-caps evenly, but to dislike large-caps relatively over time. Investors evenly favor growth- and value-oriented stocks, but tend to dislike growth stocks over time.[18]

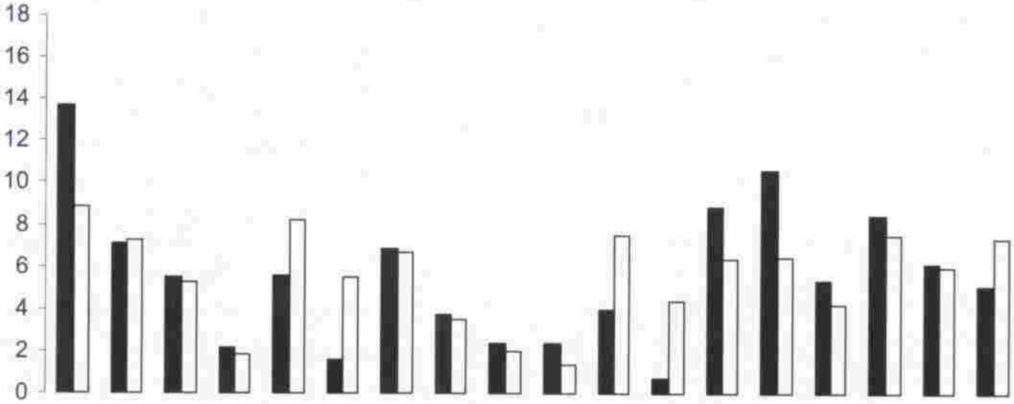
When in-favor characteristics are defined by the prior twelve-month returns of characteristics sorted portfolios, this tendency is much stronger, especially for the book-to-market characteristics. Investors generally dislike growth stocks and favor value stocks. This is consistent with the common perception that value strategies take a long time to become profitable. Although small value stocks and medium-cap value stocks are more often favored than disfavored by investors, the frequency distribution in Table 4 is not particularly spiked in certain characteristics. The evidence that the in- and out-of-favor characteristics are dominated by a few characteristics is not very strong overall.

Is Characteristics Momentum Distinctive?

Before identifying the sources of the predictability of future stock returns based on in- or out-of-favor characteristics, we examine whether the continuation in in-favor styles (characteristics) is independent from the continuation in price movements documented by Jegadeesh and Titman [1993] and in industry movements documented by Moskowitz and Grinblatt [1999].

Table 4. *Distribution of In-Favor and Out-of-Favor Characteristics*

Panel A: Ranking variable: past 3-month returns



Size (Group 1: Small, Group 2: Medium, Group 3: Large)
1 1 1 1 1 1 2 2 2 2 2 2 3 3 3 3 3 3
Book-to-Market (Group 1: Growth, Group 2: Medium, Group 3: Value)
1 1 2 2 3 3 1 1 2 2 3 3 1 1 2 2 3 3
Dividend Yield (Group 1: Low, Group 2: High)
1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2

Frequency Summary

	Size		Book-to-Market		Dividend Yield	
	Out-of-Favor	**In-Favor**	**Out-of-Favor**	**In-Favor**	**Out-of-Favor**	**In-Favor**
Group 1	35.57	36.82	50.74	39.06	58.21	54.98
Group 2	20.03	25.38	26.13	22.15	41.79	45.04
Group 3	44.41	37.82	23.13	38.82		

(continued)

Independent Two-Way Analysis

To avoid the sorting-out-sorts problem criticized by Berk [2000], an independent two-way classification[19] is used as the first way to disentangle characteristics momentum from price and industry momentum. At the beginning of each month, stocks are independently assigned to one of the three equally sized portfolios according to their individual stock returns, their associated industry returns, or their associated characteristics sorted portfolio returns over prior three- or twelve-month returns. Under this procedure, each stock is given three readings of price momentum, industry momentum, and characteristics momentum rankings. A pair of two ranking readings is examined each time, so Table 5 reports the monthly equally weighted average returns for each of nine portfolios over the holding periods of three to twelve months, and the post-holding periods of the second and third years following portfolio formation.

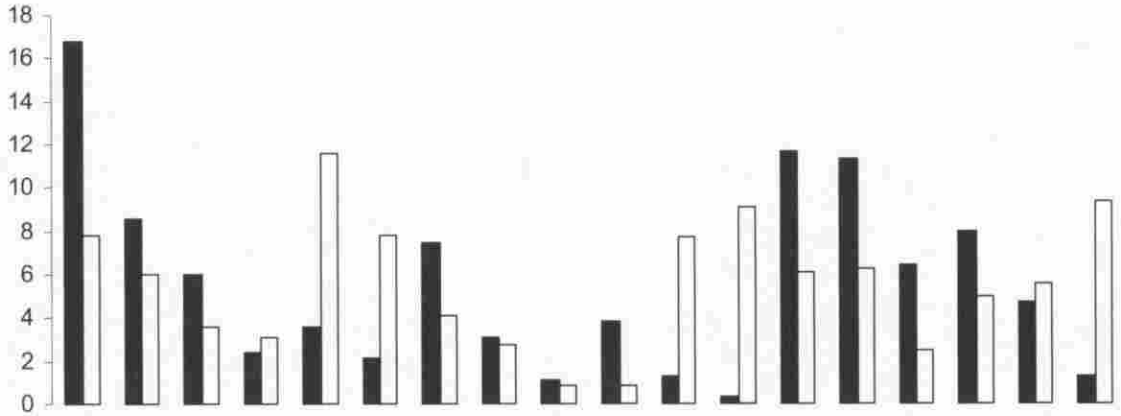
Table 5 shows that characteristics momentum strategies are strongly independent from other momentum strategies, especially when the strategies are formed based on the prior one-year returns. Particularly in the lowest rankings in terms of individual stock returns in Panel A (industry returns in Panel B), stocks with persistently in-favor characteristics outperform stocks with persistently out-of-favor characteristics by 0.789% (0.77%) per month over the following three months. Both are statistically significant and economically large. When rankings are formed by prior three-month returns, characteristics momentum strategies are comparatively indistinguishable from other strategies over three to nine months following portfolio formation, but unambiguously different over twelve months following portfolio formation.

Cross-Sectional Regressions

Fama-MacBeth [1973] cross-sectional regressions are used as the second way to disentangle price, industry, and characteristics momentum strategies. Every month, a cross-sectional regression of individual stock

Table 4. *(Continued)*

Panel B: Ranking variable: past 12-month returns



Size (Group 1: Small, Group 2: Medium, Group 3: Large)

1 1 1 1 1 1 2 2 2 2 2 2 3 3 3 3 3 3

Book-to-Market (Group 1: Growth, Group 2: Medium, Group 3: Value)

1 1 2 2 3 3 1 1 2 2 3 3 1 1 2 2 3 3

Dividend Yield (Group 1: Low, Group 2: High)

1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2 1 2

Frequency Summary

	Size		**Book-to-Market**		**Dividend Yield**	
	Out-of-Favor	**In-Favor**	**Out-of-Favor**	**In-Favor**	**Out-of-Favor**	**In-Favor**
Group 1	39.43	39.92	58.96	32.96	59.08	49.87
Group 2	17.17	25.37	27.74	15.92	40.93	50.13
Group 3	43.41	34.71	13.31	51.12		

Note: At the beginning of every month from July 1964 through December 1997, eighteen ME-BM-DY sorted portfolios are ranked by their prior three-month or twelve-month compounded returns. The stocks in the top two ranking portfolios have prior in-favor characteristics, while stocks in the bottom two ranking portfolios have out-of-favor characteristics. The figure and table present the percentage frequency of these eighteen portfolios by which their characteristics are favored (indicated by white bar) or disfavored (indicated by black bar) by investors over the sample period.

returns on price momentum (PM), industry momentum (IM), and characteristics momentum (CM) rankings is fitted.[20] The PM rankings are constructed on the basis of an individual stock's prior compounded returns, while the CM rankings are constructed on the basis of the prior returns of the partition cell to which the stock is assigned. In a manner similar to that in Moskowitz and Grinblatt [1999], the IM rankings are constructed on the basis of the prior compounded returns of industries, where value-weighted returns of twenty industries classified by SIC codes are updated monthly.

Panel A of Table 6 reports the time series averages of the slope coefficients and the associated Newey-West adjusted t-statistics of Fama-MacBeth cross-sectional regressions for ranking periods three to twelve months and holding periods of one to thirty-six months. Because of potential microstructure effects, such as bid-ask bounce and liquidity effects, there is a one-month return reversal for individual stocks when rankings are formed by prior three-month returns. In addition, the IM ranking is very strong relative to other momentum rankings in predicting a future one-month return when rankings are formed by prior three- or six-month returns. These results are consistent with Moskowitz and Grinblatt [1999].[21]

However, when we consider future returns of longer than nine months, the explanatory power of CM increases, and decreases for both PM and IM. Furthermore, the explanatory power of both PM and IM diminish completely when the holding period is beyond a year. Surprisingly, the CM rankings have the strongest predictive power on the subsequent three-year return when the rankings are formed by prior twelve-month returns. These indicate that CM tends to have longer-lasting effects than PM or IM.

The explanatory powers of PM, CM, and IM are obscured if the correlation between these regressors is

Table 5. *Disentangling Momentum Strategies—Independent Two-Way Sorting*

Panel A: Price Momentum versus Characteristics Momentum

	Holding Months					
K =	3	6	9	12	2nd Year	3rd Year
Ranking Variable: Prior Three-Month Compounded Returns						
(1, 1)	1.437	1.446	1.507	1.554	1.273	1.365
(1, 2)	1.333	1.431	1.452	1.462	1.327	1.393
(1, 3)	1.110	1.290	1.317	1.309	1.241	1.303
(1, 1)–(1, 3)	0.327	0.156	0.190	0.245	0.032	0.062
	(2.62)	(1.27)	(1.66)	(2.44)	(0.39)	(0.59)
(2, 1)	1.509	1.452	1.425	1.465	1.370	1.400
(2, 2)	1.366	1.390	1.368	1.372	1.370	1.385
(2, 3)	1.061	1.181	1.186	1.148	1.270	1.261
(2, 1)–(2, 3)	0.448	0.271	0.239	0.317	0.100	0.139
	(3.48)	(2.28)	(2.25)	(3.42)	(1.19)	(1.40)
(3, 1)	1.428	1.278	1.250	1.289	1.437	1.530
(3, 2)	1.322	1.243	1.216	1.210	1.493	1.480
(3, 3)	1.052	1.062	1.022	0.946	1.405	1.401
(3, 1)–(3, 3)	0.376	0.216	0.228	0.343	0.032	0.129
	(2.46)	(1.56)	(1.87)	(3.33)	(0.31)	(1.08))
Ranking Variable: Prior Twelve-Month Compounded Returns						
(1, 1)	1.862	1.762	1.679	1.593	1.309	1.387
(1, 2)	1.691	1.675	1.622	1.561	1.323	1.372
(1, 3)	1.374	1.338	1.279	1.242	1.163	1.223
(1, 1)–(1, 3)	0.488	0.424	0.400	0.351	0.146	0.164
	(3.74)	(3.26)	(3.17)	(2.84)	(1.04)	(1.27)
(2, 1)	1.606	1.601	1.601	1.559	1.496	1.453
(2, 2)	1.296	1.333	1.342	1.362	1.376	1.398
(2, 3)	0.878	0.959	0.980	1.007	1.162	1.228
(2, 1)–(2, 3)	0.728	0.642	0.621	0.552	0.334	0.225
	(5.41)	(4.80)	(4.83)	(4.28)	(2.16)	(1.85)
(3, 1)	1.308	1.312	1.366	1.407	1.623	1.656
(3, 2)	1.009	1.094	1.166	1.264	1.516	1.600
(3, 3)	0.519	0.661	0.733	0.839	1.293	1.437
(3, 1)–(3, 3)	0.789	0.651	0.633	0.568	0.330	0.219
	(4.98)	(4.36)	(4.36)	(3.72)	(1.70)	(1.40)

Panel B: Industry Momentum versus Characteristics Momentum

	Holding Months					
K =	3	6	9	12	2nd Year	3rd Year
Ranking Variable: Prior Three-Month Compounded Returns						
(1, 1)	1.670	1.557	1.578	1.595	1.268	1.344
(1, 2)	1.609	1.563	1.539	1.510	1.352	1.394
(1, 3)	1.474	1.464	1.435	1.356	1.307	1.309
(1, 1)–(1, 3)	0.196	0.092	0.143	0.239	–0.039	0.035
	(1.30)	(0.66)	(1.10)	(2.22)	(–0.47)	(0.32)
(2, 1)	1.447	1.434	1.458	1.511	1.444	1.450
(2, 2)	1.390	1.415	1.413	1.416	1.453	1.438
(2, 3)	1.188	1.286	1.257	1.195	1.349	1.372
(2, 1)–(2, 3)	0.259	0.148	0.200	0.316	0.095	0.078
	(1.81)	(1.13)	(1.68)	(3.02)	(1.05)	(0.74)
(3, 1)	1.402	1.384	1.359	1.416	1.434	1.482
(3, 2)	1.221	1.276	1.264	1.289	1.454	1.456
(3, 3)	0.858	0.994	1.015	0.987	1.358	1.339
(3, 1)–(3, 3)	0.544	0.390	0.344	0.429	0.076	0.142
	(3.65)	(2.95)	(2.98)	(4.23)	(0.70)	(1.22)

(continued)

Table 5. *(continued)*

Panel B: Industry Momentum versus Characteristics Momentum						
	Holding Months					
K =	3	6	9	12	2nd Year	3rd Year
Ranking Variable: Prior Twelve-Month Compounded Returns						
(1, 1)	1.877	1.760	1.694	1.606	1.308	1.432
(1, 2)	1.638	1.620	1.586	1.558	1.371	1.483
(1, 3)	1.301	1.290	1.243	1.226	1.211	1.347
(1, 1)–(1, 3)	0.576	0.470	0.450	0.379	0.097	0.084
	(3.55)	(3.17)	(3.18)	(2.77)	(0.63)	(0.59)
(2, 1)	1.683	1.627	1.616	1.564	1.484	1.506
(2, 2)	1.440	1.453	1.448	1.471	1.421	1.486
(2, 3)	1.051	1.069	1.056	1.081	1.245	1.312
(2, 1)–(2, 3)	0.632	0.558	0.560	0.483	0.239	0.194
	(4.10)	(3.61)	(3.65)	(3.16)	(1.46)	(1.28)
(3, 1)	1.470	1.538	1.573	1.590	1.599	1.459
(3, 2)	1.151	1.273	1.312	1.371	1.456	1.424
(3, 3)	0.699	0.840	0.887	0.954	1.269	1.325
(3, 1)–(3, 3)	0.770	0.698	0.686	0.637	0.330	0.134
	(5.01)	(4.88)	(4.90)	(4.30)	(1.79)	(0.85)

Note: At the beginning of every month from July 1964 through December 1997, nine portfolios are formed based on stock price momentum rankings (PMR), characteristics momentum rankings (CMR), and industry momentum rankings (IMR). In PMR, all NYSE, AMEX, and Nasdaq stocks are assigned an integer from 1 (winner) to 3 (loser) depending on the stock's prior three-month or twelve-month compounded returns. Stocks in the top (bottom) thirty-third percentile rankings are assigned a 1 (3), while stocks in the middle thirty-fourth percentile rankings are given a 2. In CMR, the eighteen ME-BM-DY sorted portfolios are also ranked by their prior three-month or twelve-month compounded returns. Stocks in the top six ranking portfolios are labeled 1 (winner), while stocks in the bottom six ranking portfolios are labeled 3 (loser). Stocks in the middle six ranking portfolios are labeled 2. In IMR, the twenty industry portfolios (twenty value-weighted industry portfolios are formed monthly from July 1963 through December 1997 using two-digit SIC codes from CRSP. See Moskowitz and Grinblatt [1999] for details) are also ranked by their prior three-month or twelve-month compounded returns. Stocks in the bottom seven ranking portfolios are given a 3, while stocks in the top seven ranking portfolios are given a 1. Stocks in the middle six portfolios are assigned a 2. Each stock gets two readings in the winner-loser identification, so nine portfolios (3×3) are formed. In Panel A, the first reading in the pair indicates the ranking of the price momentum, the second indicates the ranking of the characteristics momentum. In Panel B, the first reading indicates the ranking of the industry momentum and the second the ranking of the characteristics momentum. The portfolios are held for K subsequent months ($K = 3, 6, 9$, and 12), and for months in the second and third year following the formation. All stocks are equally weighted in the portfolios. The average monthly returns of these portfolios are presented as a percentage. The t-statistics with the Newey-West estimators adjusted for standard errors are reported in parentheses.

unreasonably high. In an unreported result, we examine this issue by calculating the Pearson correlation.[22] For the twelve-month/twelve-month strategy, the correlations between PM and IM, IM and CM, and PM and CM are 0.198, 0.087, and 0.118, respectively. For the three-month/three-month strategy, the correlations are 0.169, 0.112, and 0.179, respectively. The low correlations suggest that the different momentum variables are not entirely based on the same information. Rather, they capture different aspects of improvement or deterioration in a company's performance.

To more fully purge the cross-section from any confounding influences related to PM and IM over various prior return horizons, we report the results after taking out industry's return on the left-hand side of the regressions in Panel B of Table 6.[23] Specifically, the industry-adjusted return for a stock is defined as the return on the stock minus the return on the industry-matched portfolio to which it was assigned at the time of portfolio formation. This would account for IM at all past return horizons. Again, the result clearly shows that the explanatory power of CM is robust in terms of magnitude and significance, and that it has longer-lasting effects.

For a robustness check, we replace the eighteen ME-BM-DY sorted portfolios with the twenty-five ME-BM sorted portfolios in constructing CM rankings in Panel C of Table 6 and repeat the same test. To have a meaningful comparison, stocks are assigned to the same range of ranking scores in both characteristics partitions. Again, the significant predictive power of CM rankings to a stock's future industry-adjusted returns appears.

Adjustment for Time-Varying Factor Exposures

Grundy and Martin [2001] show that the PM strategy loads investors up on the factors that have done well recently. By considering the issue of time-varying factor exposures in Table 7, we further examine whether the CM profits exist after adjusting for PM, which might capture changes in investor sentiment

Table 6. *Disentangling Momentum Strategies - Fama-MacBeth Cross-Sectional Regression*

Panel A: Using Raw Returns in the Dependent Variable
The Cross-Sectional Regression: $R_i = \alpha + \beta_p PM_i + \beta_I IM_i + \beta_c CM_i^{3\times3\times2} + \epsilon_i$

Ranking By Prior 3-Month Returns			Ranking By Prior 6-Month Returns			Ranking By Prior 9-Month Returns			Ranking By Prior 12-Month Returns		
β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C
A1. Dependent Variable: Subsequent One-Month Compounded Returns											
–0.133	0.150	0.160	–0.034	0.114	0.105	0.020	0.100	0.103	0.066	0.102	0.152
(–5.04)	(10.64)	(6.28)	(–1.18)	(7.13)	(4.09)	(0.64)	(6.13)	(3.76)	(2.37)	(6.11)	(6.21)
A2. Dependent Variable: Subsequent Three-Month Compounded Returns											
0.015	0.239	0.176	0.179	0.187	0.120	0.290	0.183	0.185	0.335	0.192	0.322
(0.30)	(6.98)	(2.65)	(2.85)	(4.02)	(1.62)	(4.14)	(4.00)	(2.42)	(5.35)	(3.82)	(4.32)
A3. Dependent Variable: Subsequent Six-Month Compounded Returns											
0.235	0.328	0.173	0.494	0.323	0.222	0.659	0.309	0.402	0.570	0.271	0.555
(3.32)	(5.37)	(1.50)	(4.79)	(3.67)	(1.61)	(5.98)	(3.17)	(2.84)	(5.21)	(2.45)	(3.50)
A4. Dependent Variable: Subsequent Nine-Month Compounded Returns											
0.469	0.475	0.262	0.791	0.447	0.466	0.801	0.386	0.630	0.656	0.327	0.873
(5.29)	(5.48)	(1.68)	(6.24)	(3.62)	(2.37)	(5.70)	(2.54)	(3.13)	(4.47)	(1.97)	(3.70)
A5. Dependent Variable: Subsequent Twelve-Month Compounded Returns											
0.656	0.523	0.530	0.814	0.443	0.641	0.756	0.367	0.840	0.564	0.297	1.091
(6.77)	(4.62)	(2.69)	(5.46)	(2.80)	(2.55)	(4.39)	(1.85)	(3.30)	(3.12)	(1.36)	(3.40)
A6. Dependent Variable: Subsequent Twenty-Four-Month Compounded Returns											
0.155	0.385	0.847	0.218	0.271	1.248	0.125	0.114	1.788	–0.085	–0.006	2.326
(0.82)	(1.97)	(2.23)	(0.77)	(1.03)	(2.66)	(0.38)	(0.36)	(3.43)	(–0.22)	(–0.02)	(3.23)
A7. Dependent Variable: Subsequent Thirty-Six-Month Compounded Returns											
–0.352	0.030	1.700	–0.351	0.034	2.381	–0.597	0.013	3.027	–0.955	–0.088	3.400
(–1.42)	(0.11)	(3.09)	(–0.92)	(0.09)	(3.21)	(–1.30)	(0.03)	(3.36)	(–1.69)	(–0.18)	(3.23)

Panel B: Using Industry-Adjusted Returns in the Dependent Variable
The Cross-Sectional Regression: $R_i - R_{Industry} = \alpha + \beta_p PM_i + \beta_I IM_i + \beta_c CM_i^{3\times3\times2} + \varepsilon_i$

Ranking by Prior 3-Month Returns			Ranking by Prior 6-Month Returns			Ranking by Prior 9-Month Returns			Ranking by Prior 12-Month Returns		
β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C
B1. Dependent Variable: Subsequent One-Month Industry-Adjusted Compounded Returns											
–0.139	0.075	0.156	–0.034	0.061	0.102	0.017	0.045	0.107	0.060	0.028	0.144
(–5.36)	(4.77)	(6.79)	(–1.24)	(4.28)	(4.40)	(0.56)	(2.84)	(4.48)	(2.27)	(1.71)	(6.70)
B2. Dependent Variable: Subsequent Three-Month Industry-Adjusted Compounded Returns											
0.011	0.142	0.173	0.176	0.112	0.125	0.279	0.054	0.192	0.320	0.033	0.303
(0.22)	(4.26)	(2.91)	(2.98)	(3.10)	(1.91)	(4.25)	(1.30)	(2.88)	(5.45)	(0.73)	(4.68)
B3. Dependent Variable: Subsequent Six-Month Industry-Adjusted Compounded Returns											
0.231	0.159	0.180	0.481	0.104	0.227	0.634	0.013	0.403	0.548	0.015	0.515
(3.48)	(3.28)	(1.74)	(5.09)	(1.65)	(1.85)	(6.28)	(0.16)	(3.23)	(5.47)	(0.19)	(3.71)
B4. Dependent Variable: Subsequent Nine-Month Industry-Adjusted Compounded Returns											
0.455	0.128	0.260	0.771	0.046	0.450	0.775	–0.018	0.607	0.632	–0.005	0.805
(5.59)	(1.98)	(1.83)	(6.80)	(0.51)	(2.54)	(6.13)	(–0.16)	(3.41)	(4.75)	(–0.04)	(3.86)
B5. Dependent Variable: Subsequent Twelve-Month Industry-Adjusted Compounded Returns											
0.642	0.107	0.487	0.807	0.046	0.599	0.741	-0.020	0.795	0.548	-0.002	1.007
(7.44)	(1.32)	(2.72)	(6.13)	(0.40)	(2.65)	(4.84)	(-0.15)	(3.52)	(3.34)	(-0.01)	(3.51)

(continued)

Table 6. *(continued)*

Panel B: Using Industry-Adjusted Returns in the Dependent Variable
The Cross-Sectional Regression: $R_i - R_{Industry} = \alpha + \beta_p PM_i + \beta_I IM_i + \beta_c CM_i^{3\times3\times2} + \varepsilon_i$

Ranking by Prior 3-Month Returns			Ranking by Prior 6-Month Returns			Ranking by Prior 9-Month Returns			Ranking by Prior 12-Month Returns		
β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C
B6. Dependent Variable: Subsequent Twenty-Four-Month Industry-Adjusted Compounded Returns											
0.184	0.159	0.778	0.266	0.143	1.166	0.140	0.083	1.694	-0.083	0.045	2.165
(1.06)	(1.10)	(2.24)	(1.05)	(0.75)	(2.76)	(0.47)	(0.38)	(3.65)	(-0.23)	(0.18)	(3.36)
B7. Dependent Variable: Subsequent Thirty-Six-Month Industry-Adjusted Compounded Returns											
−0.289	0.003	1.579	−0.265	−0.048	2.258	−0.543	−0.137	2.856	−0.919	−0.157	3.174
(−1.25)	(0.01)	(3.12)	(−0.77)	(−0.19)	(3.38)	(−1.31)	(−0.46)	(3.51)	(−1.79)	(−0.45)	(3.36)

Panel C: Using Industry-Adjusted Returns in the Dependent Variable
The Cross-Sectional Regression: $R_i - R_{Industry} = \alpha + \beta_p PM_i + \beta_I IM_i + \beta_c CM_i^{5\times5} + \varepsilon_i$

Ranking by Prior 3-Month Returns			Ranking by Prior 6-Month Returns			Ranking by Prior 9-Month Returns			Ranking by Prior 12-Month Returns		
β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C	β_P	β_I	β_C
C1. Dependent Variable: Subsequent One-Month Industry-Adjusted Compounded Returns											
−0.018	0.037	0.086	−0.003	0.021	0.039	0.001	0.012	0.035	0.004	0.006	0.041
(−5.24)	(4.56)	(6.17)	(−1.34)	(3.95)	(4.31)	(0.51)	(2.52)	(5.08)	(2.45)	(1.33)	(8.74)
C2. Dependent Variable: Subsequent Three-Month Industry-Adjusted Compounded Returns											
0.000	0.077	0.097	0.014	0.040	0.054	0.018	0.012	0.078	0.017	0.004	0.091
(0.04)	(4.49)	(2.69)	(2.55)	(3.01)	(2.06)	(3.57)	(0.92)	(3.79)	(5.26)	(0.38)	(6.15)
C3. Dependent Variable: Subsequent Six-Month Industry-Adjusted Compounded Returns											
0.024	0.087	0.097	0.040	0.033	0.103	0.042	−0.006	0.152	0.029	−0.009	0.156
(2.65)	(3.28)	(1.53)	(4.29)	(1.32)	(2.16)	(5.13)	(−0.23)	(4.17)	(5.11)	(−0.41)	(5.04)
C4. Dependent Variable: Subsequent Nine-Month Industry-Adjusted Compounded Returns											
0.051	0.075	0.160	0.063	0.013	0.179	0.049	−0.018	0.211	0.032	−0.018	0.229
(4.39)	(2.01)	(1.78)	(5.18)	(0.37)	(2.57)	(4.99)	(−0.54)	(4.17)	(4.26)	(−0.63)	(4.75)
C5. Dependent Variable: Subsequent Twelve-Month Industry-Adjusted Compounded Returns											
0.074	0.068	0.263	0.065	0.016	0.214	0.048	−0.024	0.255	0.031	−0.023	0.272
(5.68)	(1.44)	(2.55)	(4.82)	(0.37)	(2.54)	(4.32)	(−0.59)	(4.04)	(3.49)	(−0.62)	(4.15)
C6. Dependent Variable: Subsequent Twenty-Four-Month Industry-Adjusted Compounded Returns											
0.008	0.078	0.363	0.014	0.018	0.390	0.012	−0.024	0.527	0.004	−0.024	0.584
(0.26)	(0.93)	(1.72)	(0.48)	(0.24)	(2.30)	(0.48)	(−0.36)	(3.95)	(0.20)	(−0.41)	(3.71)
C7. Dependent Variable: Subsequent Thirty-Six-Month Industry-Adjusted Compounded Returns											
−0.050	−0.029	0.804	−0.019	−0.102	0.853	−0.017	−0.156	0.966	−0.031	−0.122	0.908
(−1.36)	(−0.23)	(2.61)	(−0.56)	(−0.92)	(3.23)	(−0.61)	(−1.54)	(3.89)	(−1.29)	(−1.36)	(3.56)

Note: At the beginning of every month from July 1964 through December 1997, cross-sectional regressions are estimated from individual stock future returns on three momentum ranking variables. The reported statistics are the time series average coefficients from the month-by-month regressions. t-statistics with the Newey-West estimators adjusted for standard errors are in parentheses. In the price momentum (PM) rankings, all NYSE, AMEX, and Nasdaq stocks are assigned to one of nine equal-size portfolios by the stocks' prior three-month (or six-, nine-, or twelve-month) compounded returns. Stocks in the portfolio at the bottom ranking are given a 1, while stocks in the portfolio at the top ranking are given a 9. Stocks in the middle portfolios are assigned from 2 to 8 in ascending order. In the industry momentum (IM) rankings, the twenty industry portfolios are sorted by their prior three-month (or six-, nine-, or twelve-month) compounded returns. Stocks in the portfolio at the bottom three ranking are given a 1, while stocks in the portfolio at the top three rankings are given a 9. In the characteristics momentum (CM3×3×2) rankings, the eighteen ME-BM-DY sorted portfolios are ranked by their prior three-month (or six-, nine-, or twelve-month) compounded returns in ascending order. Stocks in the bottom two ranking portfolios are labeled 1, while stocks in the top two ranking portfolios are labeled 9. In both IM and CM3×3×2, stocks in the middle two-sequential portfolios are assigned from 2 to 8. *Raw* returns over the subsequent months are used in Panel A as the dependent variable, while industry-adjusted compounded returns are used in Panel B. In Panel C, we perform the characteristics momentum (CM5×5) rankings based on the portfolios formed by quintile size and book-to-market in a similar manner. Stocks in the bottom three ranking portfolios are labeled 1, while stocks in the top three ranking portfolios are labeled 9. Stocks in the middle two- or three-sequential portfolios are assigned from 2 to 8.

Table 7. *Adjusted Returns of Characteristics Momentum Strategies*

	Holding Months					
K =	3	6	9	12	2nd Year	3rd Year
Panel A: Strategies Formed by Prior Three-Month Compounded Returns of 3 × 3 × 2 Style Portfolios						
Raw Returns	0.373	0.271	0.335	0.442	0.051	0.083
	(2.00)	(1.72)	(2.47)	(3.67)	(0.47)	(0.61)
Price-Adjusted	0.246	0.198	0.247	0.355	–0.051	–0.054
	(1.74)	(1.60)	(2.51)	(4.01)	(–0.46)	(–0.41)
Industry-Adjusted	0.352	0.268	0.306	0.384	0.069	0.104
	(2.33)	(2.04)	(2.70)	(3.83)	(0.77)	(0.95)
Panel B: Strategies Formed by Prior Twelve-Month Compounded Returns of 3 × 3 × 2 Style Portfolios						
Raw Returns	0.733	0.660	0.633	0.575	0.199	0.065
	(4.02)	(3.89)	(3.87)	(3.52)	(1.11)	(0.39)
Price-Adjusted	0.590	0.534	0.486	0.438	0.024	–0.115
	(4.61)	(4.23)	(3.84)	(3.32)	(0.13)	(–0.69)
Industry-Adjusted	0.623	0.567	0.540	0.487	0.191	0.098
	(4.27)	(4.15)	(4.06)	(3.60)	(1.31)	(0.72)
Panel C: Strategies Formed by Prior Three-Month Compounded Returns of 5 × 5 Style PortfoliosRaw Returns						
Raw Returns	0.332	0.282	0.314	0.388	–0.001	0.107
	(1.82)	(1.81)	(2.35)	(3.35)	(–0.01)	(0.76)
Price-Adjusted	0.263	0.270	0.275	0.330	–0.085	–0.028
	(1.97)	(2.28)	(2.77)	(3.80)	(–0.85)	(–0.21)
Industry-Adjusted	0.335	0.296	0.298	0.345	0.033	0.098
	(2.38)	(2.38)	(2.73)	(3.65)	(0.40)	(0.90)
	0.771	0.662	0.631	0.520	0.233	0.220
Panel D: Strategies Formed by Prior Twelve-Month Compounded Returns of 5 × 5 Style Portfolios Raw Returns						
Raw Returns	0.771	0.662	0.631	0.520	0.233	0.220
	(3.98)	(3.64)	(3.58)	(2.94)	(1.22)	(1.17)
Price-Adjusted	0.613	0.536	0.489	0.393	0.054	0.038
	(4.60)	(4.02)	(3.53)	(2.62)	(0.29)	(0.20)
Industry-Adjusted	0.718	0.650	0.611	0.508	0.231	0.203
	(4.74)	(4.52)	(4.24)	(3.44)	(1.50)	(1.39)

Note: At the beginning of every month from July 1964 through December 1997, eighteen ME-BM-DY sorted portfolios are ranked by their prior three-month or twelve-month compounded returns. The stocks in the top two ranking portfolios form a "buy" portfolio, while stocks in the bottom two form a "sell" portfolio. Both "buy" and "sell" portfolios are held for K subsequent months. All stocks are value-weighted in the portfolios. The average of monthly profits of "buy" minus "sell" momentum portfolios is reported in a percentage format. Results are reported for holding period raw, price momentum-adjusted, and industry-adjusted returns. The t-statistics with the Newey-West estimators adjusted for standard errors are reported in parentheses. In Panels C to D, we partition the stock universe into twenty-five ME-BM sorted portfolios based on quintile breakpoints of size and book-to-market of NYSE firms in a similar manner and perform the characteristics momentum strategies. Stocks in the top three ranking portfolios form a "buy" portfolio, while stocks in the bottom three form a "sell" portfolio.

about a firm's prospects, and the industry factor, which might capture changes in business sentiment about an industry's prospects.[24] The strong existence of CM profits adjusted for individual stock returns or the industry factor provides additional robust evidence that CM is distinct from PM and IM. Furthermore, the price- or industry-adjusted profits have almost the same magnitude as the raw profits for CM strategies. Therefore, it is difficult to disregard CM.

Are Characteristics Momentum Profits Abnormal?

The previous results raise the possibility that the predictive power of prior in-favor or out-of-favor characteristics may be confounded with the intrinsic effects of book-to-market or firm size. In the context of the FF [1996] three-factor model, we investigate whether the behavior of returns on the CM portfolios can be explained by factors related to size and book-to-market. In other words, we examine whether characteristics momentum contains additional predictive information about future expected returns after taking size and book-to-market fundamentals into consideration.

Table 8 reports summary statistics of time series regressions for the highest- and lowest-ranked portfolios by the prior J-month (J = 1, 3, or 12) returns. We track the monthly returns from a strategy of buying each portfolio and holding it for J months, when a new portfolio is formed and the process repeated. Ta-

Table 8. *Three-Factor Time Series Regressions Based on Monthly Excess Returns of Characteristics Momentum Strategies*

	Constant	RMRF	SMB	HML	R^2
Panel A. Extreme Performers are Defined Based on the Prior One-Month Return of their Assigned 3 × 3 × 2 Style Portfolios					
Buy	0.845	0.966	0.748	0.159	82.83
	(6.93)	(31.70)	(17.23)	(3.22)	
Sell	–0.662	1.072	0.802	0.157	82.01
	(–4.79)	(31.02)	(16.30)	(2.81)	
Buy–Sell	1.507	–0.106	–0.054	0.002	0.74
	(6.69)	(–1.87)	(–0.67)	(0.02)	
Panel B. Extreme Performers are Defined Based on the Prior Three-Month Return of their Assigned 3 × 3 × 2 Style Portfolios					
Buy	0.219	1.018	0.696	0.154	84.62
	(1.88)	(34.89)	(16.75)	(3.25)	
Sell	–0.261	1.105	0.844	0.261	80.70
	(–1.77)	(29.87)	(16.03)	(4.34)	
Buy–Sell	0.481	–0.087	–0.148	–0.107	1.26
	(2.09)	(–1.52)	(–1.82)	(–1.14)	
Panel C. Extreme Performers are Defined Based on the Prior Twelve-Month Return of their Assigned 3 × 3 × 2 Style Portfolios					
Buy	0.259	1.006	0.710	0.253	82.86
	(2.12)	(32.85)	(16.29)	(5.09)	
Sell	–0.324	0.978	0.650	0.084	82.45
	(–2.67)	(32.14)	(15.01)	(1.70)	
Buy–Sell	0.583	0.028	0.060	0.169	0.36
	(2.76)	(0.52)	(0.80)	(1.97)	

Note: The regression is estimated over monthly observations from July 1964 through December 1997. Eighteen ME-BM-DY sorted portfolios are first ranked by their prior J-month compounded returns. The stocks in the top two ranking portfolios form a "buy" portfolio, while the stocks in the bottom two ranking portfolios form a 'sell" portfolio. The portfolio is held for J months, at which time it is reformed and the strategy is repeated. The dependent variable is the monthly return of these two portfolios in excess of the Treasury bill rate. The explanatory variables are the monthly returns of the Fama and French [1996] three-factor model. Results are also shown for the difference between the two portfolios. The regression R_2 is adjusted for degree of freedom, and t-statistics are shown in parentheses.

ble 8 also reports results for the arbitrage portfolio formed by buying the highest-ranked portfolio, or the winners, and selling the lowest-ranked portfolio, or the losers.

When the ranking variable is the prior one-month return of characteristics partitions, the portfolio of extreme performers has similar risk exposures to the market, size, and book-to-market factors. This is consistent with Table 4, which shows that the in- and out-of-favor characteristics are not dominated by a few specific characteristics. The intercept for the arbitrage portfolio is 1.507% per month, with a *t*-statistic of 6.69. When the ranking variable is the prior twelve-month return of characteristics partitions, both extreme performers still have similar risk exposures to the market and size factors. However, the portfolio of winners is oriented more to value stocks. The intercept for the arbitrage portfolio is smaller but still significantly positive at 0.583% per month, with a *t*-statistic of 2.76. After adjusting for three risk factors, it seems that CM (holding a long position in stocks with in-favor characteristics and a short position in stocks with out-of-favor characteristics) conveys additional valuable information about future returns.

We can hypothesize that if past winners take greater risks than past losers, they should have worse (better) performance during bad (good) states of the world, irrespective of the underlying risk factors. We can confirm this by examining to what extent bad and good states correspond to low and high excess returns, respectively, on a broad stock market index.

In particular, when the return on the CRSP value-weighted market index falls below the monthly Treasury bill rate, riskier stocks should earn lower returns. As it turns out, during such down-market months, the return difference between the winner and loser portfolios is positive (1.43% per month when the ranking variable is the past one-month return, and 0.53% when the ranking variable is the past twelve-month return). Conversely, in up-market months, the average difference is 1.45% per month using the past one-month return, and 0.79% using the past twelve-month return. Strategies exploiting high momentum in in-favor characteristics thus seem to do especially well in up-markets.

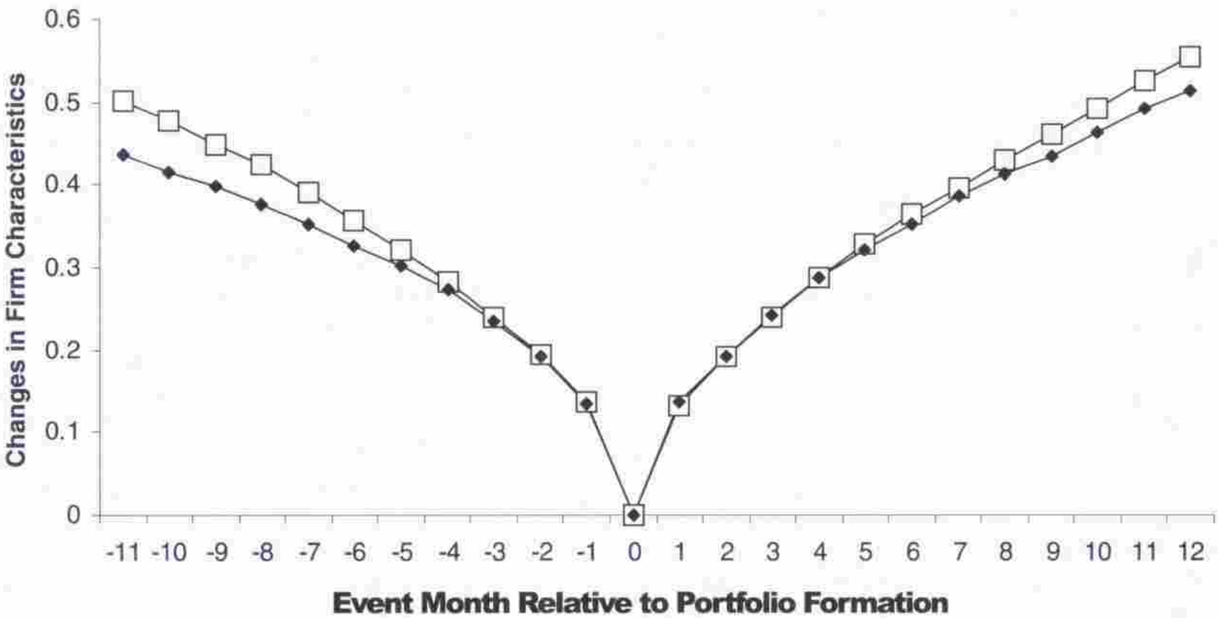
In an unreported result, when eighteen ME-BM-DY sorted portfolios are replaced by twenty-five ME-BM sorted portfolios in constructing CM strategies, the same conclusion is obtained. In any event, there is no evidence that the winner portfolio is exposed to larger downside risk. This evidence could be justification for money managers to shift toward current in-favor investment styles with the goal of improving performance.

But what causes the existence of characteristics momentum profits? Berk, Green, and Naik [1999] argue that the expected return of a firm evolves slowly as old projects die and are replaced with new ones. A momentum strategy is likely to be profitable over a horizon comparable to the average life of an investment project. Berk, Green, and Naik [1999] also argue that returns to momentum strategies are compensation for bearing systematic risks that change in predictive ways over such horizons. In other words, the existence of such profits is implicitly attributable to the dynamic evolution of expected returns resulting from the dynamics of firm characteristics that do not change too much over such horizons.

However, a recent behavioral theory proposed by Barberis and Shleifer [2001] may provide more insight into the existence of characteristics momentum.[25] In the presence of switchers who can affect asset prices by moving funds across styles, a style-level momentum strategy could be successful because good performance by a style attracts switcher flows, which drive the price even higher over a short horizon. The implicit assumption is that stocks with certain firm characteristics in forming styles cannot change those characteristics too much. If they do, the style switchers who have difficulty identifying in-favor styles cannot affect asset prices.

To further verify this implication, we examine whether the dynamics of firm characteristics change greatly over a short horizon. The change in firm characteristics for a stock is defined as the squared distance of the stock's characteristics coordinate vector at time t deviated from the stock's characteristics coordinate vector at the time of portfolio formation.[26] The time series average of such changes is

FIGURE 1
Changes in Firm Characteristics



Note: At the beginning of every month from July 1964 through December 1997, the eighteen ME-BM-DY sorted portfolios are ranked by their prior twelve-month compound returns. The stocks in the top two ranking portfolios form a "buy" portfolio, while the stocks in the bottom two ranking portfolios form a "sell" potfolio. Both "buy" and "sell" porfolios are held for twelve months before and after porfolio information. The change in firm characteristics for a stock is defined as the squared distance of the stock's coordinate vector[a] at time t deviated from the stock's coordinate vector at the time of porfolio formation. For example, large growth stocks with a high dividend yield are in favor at the beginning of April 1997. Coincidentally, Stock X, with coordinate vector (3, 1, 2), belongs to a "buy" porfolio. At a time other than portfolio information, Stock X may change characteristics to (1, 3, 1), indicating a small value stock with low dividend yield. The change in firm characteristics for Stock X in this hypothetical case would be 9, which results from the calculation of $(1-3)^2 + (3-1)^2 + (1-2)^2$. By this construction, the change in firm characteristics is bounded by the range of [0, 9]. The squared distance is then value-weighted across stocks in the porfolio of "buy" and "sell". The time series average of such changes is shown in the figure over a twelve-month period around event time 0, the time of portfolio information. The square indicates the "buy" portfolio, while the dimond indicates the "sell" portfolio.[b]

[a]In the construction of ME-BM-DY characteristics partition cells, each stock is given a vector of three coordinates ($Score_{ME}$, $Score_{BM}$, $Score_{DY}$) at any time to indicate which partition cell the stock is assigned to.

[b]It is the square of the norm of a vector in mathematics. It indicates the distance between two vectors.

shown in Figure 1 over a twelve-month period around event time 0, the time of portfolio formation. One month after portfolio formation, the stocks within the in-favor characteristics group have a scale of 0.13 in characteristics changes. We can infer that the stocks, shifting at least one distance in one of three characteristics dimensions, account for 13% of portfolio value at most. This figure is exaggerated, however, since the distance is squared in the calculation.

After the first month, the changes in firm characteristics are at an incremental marginal rate of about 3% to 5%. These changes are not as great as in the out-of-favor characteristics group, and the difference between the two groups is negligible. In addition, the pattern of changes in firm characteristics is very similar in the pre- and post-ranking periods. Overall, the evidence confirms that the evolution of changes in firm characteristics is very slow over short horizons. Therefore, momentum strategies based on the return movement of style portfolios formed by firm characteristics can be performed to explore profit opportunities over short horizons.

Conclusion

This paper investigates whether investors can use equity style cycle information to enhance returns. We show that style portfolios formed by firm characteristics such as size, book-to-market, and dividend yield can be used to determine investment style dominance. There seem to be profitable trading strategies that result from selecting stocks with consistent in- or out-of-favor characteristics. For example, the zero-cost strategy, a long position at stocks with in-favor characteristics and a short position at stocks with out-of-favor characteristics over the prior year, yields 0.782% per month over the following three months. Such a characteristics momentum is distinct from the phenomena of price momentum and industry momentum, and has strong independent predictive power for future returns. More importantly, characteristics momentum has longer-lasting effects than either price or industry momentum.

The existence of characteristics momentum can be justified by the findings of Berk, Green, and Naik [1999] and Barberis and Shleifer [2001]. Berk, Green, and Naik [1999] argue that the expected returns of a firm evolve slowly as existing projects die and are replaced with new ones. Since firms with the same characteristics have similar relative systematic risks and growth potentials, they tend to be at a similar stage of the investment cycle. As a result, the dynamic evolution of expected returns on these firms will appear similar.[27] Because past returns are a measure of expected returns, which do not change much over a horizon and are comparable to the average life of an investment project, characteristics momentum profits exist over such a horizon.

Barberis and Shleifer [2001] argue that in the presence of switchers who can affect asset prices by moving funds across styles, a style-level momentum strategy could be successful because good performance by a style attracts switcher flows, which then drive the price even higher. At the same time, switchers finance a shift into successful styles by withdrawing resources from poorer-performing ones, further depressing the price of stocks with an out-of-favor style. The premise that switchers can be successful in moving money across in-favor styles is that stocks with certain firm characteristic-forming styles cannot change their characteristics too much over a short horizon.

To explain the existence of characteristics momentum profits, we document evidence that the evolution of changes in firm characteristics is very slow over short horizons. Differentiating between these two explanations may prove to be a fruitful area of academic research. For now, we leave these potential explanations as preliminary conjectures that warrant further inquiry.

In addition, the results of this study do not depend on whether twenty-five ME-BM sorted portfolios or eighteen ME-BM-DY sorted portfolios are used to perform characteristics momentum strategies. The robustness of the results across ME-BM and ME-BM-DY sorted portfolios raises another interesting issue for further future research: the interaction between the number of firm characteristics used for forming investment styles and the number of style portfolios. Obviously, there is a trade-off between these two numbers in quantifying the dynamics of firm characteristics and identifying the movement of in- and out-of-favor characteristics. This issue becomes more important when such dynamics of firm characteristics are too volatile to be quantified, especially for companies with few tangible assets and high potential growth opportunities. We leave this for future research.

Acknowledgments

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was presented at 1999 EFA conference. The paper was awarded at the 7th annual academic competition at the 2000 CQA conference.

Notes

1. Peter Lynch was the portfolio manager of the Fidelity Magellan Fund during the 1970s and 1980s. Obviously, Lynch's brilliance consisted in shifting the allocation of his fund's many holdings to investment styles with superior future potential.
2. In practice, there are some attempts to capture such opportunities. Birch [1995] describes how a plan sponsor can use style cycle information to manage equity style exposure. Fisher, Toms, and Blount [1995] use six equally weighted style portfolios to show the cyclical nature of each style's performance. However, both fail to show what pervasive forces drive style dominance and what kinds of trading strategies can be made based on this information.
3. The attraction to unbeatable Internet stocks over the last quarter of 1999 and the beginning of 2000 and the big sell-off of Internet stocks from the late first quarter to the end of 2000 are perhaps the latest manifestation of such behavior. These stocks are most likely classified as growth stocks during the bubble period in this study. According to Morningstar Inc., technology sector funds had $168.6 billion in assets at the market's peak in March 2000. Six months before the peak, tech fund assets were just $58.8 billion.
4. Henriksson [1984], Connor and Korajczyk [1991], Ferson and Schadt [1996], and Chan, Chen, and Lakonishok [2002].
5. In a contemporary study, Barberis and Shleifer [2003] demonstrate in a simulation that style-level momentum strategies are profitable in the presence of switchers who can affect asset prices by moving funds across styles. During each period, switchers allocate more funds to styles with better than average performance. They finance these additional investments by taking funds away from styles with below-average performance.
6. ME (price per share times number of common shares outstanding) is from CRSP. BM is the ratio of book value of common equity to market capitalization of equity. Book value is measured as Compustat Annual Data Item 60. DY is the ratio of common dividend (Compustat Annual Data Item 21) to market value of common equity. We consider only ordinary common equity issues with a CRSP share type code of 10 and 11. Firms with a negative book value or a price below $1 at the time of portfolio formation are excluded from the calculation to ensure that our results are not driven by extreme price movements in these low price stocks. It also avoids any confounding effect associated with stocks with a negative book value being arbitrarily assigned to value stocks. In an effort to avoid using information not available to market participants, this study restricts itself to using the accounting numbers starting four months after the end of the latest fiscal year.
7. Since we use breakpoints based only on NYSE stocks and perform independent sorting, we can have a reasonable number of firms in the partition cell with large value and low dividend yield characteristics by using the top fortieth percentile.
8. For example, stock A, labeled a big stock at the end of September 1987, would be labeled a small stock at the end of October 1987 if compared to the September NYSE breakpoint.
9. Book values are only available annually, but market values are updated monthly. Because of the constant numerator in the book-to-market ratio during the year, it might seem that a stock becoming larger would be artificially assigned to a growth-oriented partition cell during a year in the monthly portfolio forming procedure. But this would *not* happen, because the assignment is based on the *contemporaneous* book-to-market breakpoints of all NYSE firms. Therefore, the stock could be assigned to a growth-oriented or a value-oriented partition cell depending on changes in book-to-market of the stock *relative to* changes in the breakpoints during the year. The same argument can be applied to the monthly dividend yield comparison.
10. This concept is also adopted in Brown and Goetzmann [1997]. They quantify the number of relevant mutual fund investment styles by using the *k-means* cluster approach to minimize the squared differences within groups of k characteristics.
11. The change in portfolio composition is the maximum value of "in" and "out." "In" measures the proportion of stocks that are in the portfolio in month t but not in month $t-1$. "Out" measures the proportion of stocks that are in the portfolio in month t, but not in month $t+1$. These turnovers are calculated each June and December and are averaged over time.
12. The result does not change when using the alternative benchmark such as the CAPM model or Connor and Korajczyk's [1991] five statistical factors. The result is available upon request.
13. The results of forecast errors from a rolling window of past one- and three-year monthly returns are similar, and not reported here for brevity. In general, forecast quality improves as the regression estimation period lengthens. We thank Gene Fama for providing monthly returns of three factors from July 1963 to December 1997.
14. To construct the 5×5 partition, we independently place the universe of stocks into quintile portfolios based on their market capitalization and book-to-market ratio relative to contemporaneous NYSE quintile breakpoints.
15. For brevity, the result is not reported but is available upon request. For a robustness check, we also examine whether the greater prediction power of the style portfolios over the FF model still exists in *certain* periods of the market cycle. The forecast errors are always larger when the stock market outperforms the short-term bond market. The forecast error in the one-month-(five-year) ahead is larger when small-caps outperform (underperform) large-caps and when growth stocks outperform (underperform) value stocks. In any of these periods, however, the SPC still predicts future returns with fewer absolute prediction errors.
16. Several reasons may explain why the style portfolios formed by firm characteristics do better than the FF regression approach in predicting future returns. First, factor loadings obtained in the regression are biased in some systematic ways, and a reversal in factor loadings might lead to such a result. We investigate this by examining the prediction errors instead of the absolute prediction errors but find no supportive evidence. Second, the frequency of portfolio formation might be a factor; this study reforms the portfolios on a monthly basis, while FF portfolios are recast every year. This explanation appears weak, however, after we conduct the same test in Table 2 and reform the portfolios on an annual basis. The result is the same, although the absolute prediction error increases for the style portfolios. For example, the error is 7.563% for the one-month-ahead forecast and 7.569% for the six-month-ahead forecast. The final but most important explanation is that future factor loadings are imprecisely extrapolated from the past, and that firm characteristics rather than factor loadings represent the underlying pervasive force in determining a stock's expected returns.
17. Average turnovers for the buy and sell sides of the zero-cost portfolios are 85.2% and 83.4%, respectively.
18. Over the sample period, growth stocks are in favor at a rate of 39.06%, while value stocks are in favor at a rate of 38.82%. However, the frequency of growth stocks appearing out of fa-

vor is 50.74%, indicating that growth stocks have the poorest three-month prior returns 204 times out of the entire 402 months.

19. An independent two-way classification is important to distinguish the explanatory power for future returns from two variables that are both perceived to be correlated. A dependent sorting, where stocks are sorted by one variable and then sorted within the first sort by another variable, cannot accomplish such a task. The extreme groups sorted by the second variable may not be extreme any more in terms of this variable universally. As a result, this variable in the dependent two-way sorting would no longer have any explanatory ability. However, it may be that both variables can substitute for each other in explaining future returns. The test using industry-neutral portfolios to differentiate industry momentum and price momentum in Moskowitz and Grinblatt [1999] suffers from this kind of problem. In a similar argument, Berk [2000] shows that reduced within-group cross-sectional variation in expected returns coupled with model error may explain why Daniel and Titman [1997] fail to find a discernible relationship between factor loadings and returns.
20. Although using the momentum rankings rather than the raw returns as explanatory variables can reduce a bias related to the outlier statistical problem, for a robustness test, we repeat the test by using the raw return. The result is almost identical except for the magnitude of coefficient estimates, and is available upon request.
21. They find that the IM strategy subsumes the PM strategy in explaining the individual stock's size-BE/ME-adjusted returns one month ahead when the momentum strategy is formed based on prior six-month returns, but not on prior twelve-month returns.
22. Every month we calculate the Pearson correlation of a pair of regressors in a form of rankings or raw returns and then compute the time series average. The result is available upon request.
23. We wish to thank an anonymous referee for this suggestion. We also perform a robustness check by using the raw returns instead of rankings as explanatory variables in Table 7. The result is very similar and is available upon request.
24. Price momentum is constructed in a manner similar to the characteristics partition approach. Every month stocks are assigned to one of nine portfolios according to their prior three- or twelve-month returns, and value-weighted returns of each portfolio are calculated. The price momentum-adjusted return for a stock is defined as the return on the stock minus the return on the past return-matched portfolio to which the stock is assigned at the time of portfolio formation. Industry returns are constructed similarly to that in Moskowitz and Grinblatt [1999]. Every month stocks are assigned to one of twenty industries by SIC codes, and the value-weighted returns of each industry are calculated. The industry-adjusted return for a stock is defined as the return on the stock minus the return on the industry-matched portfolio to which the stock is assigned at the time of portfolio formation.
25. Following Equation (9) of Moskowitz and Grinblatt [1999], CM profits can be expressed as

$$\frac{1}{18}\sum_{c=1}^{18} E\left[(\tilde{R}_{ct}-\bar{R}_t)(\tilde{R}_{ct-1}-\bar{R}_{t-1})\right] = \sigma^2_{\mu_c} + \psi_c Cov(\tilde{R}_{P(Z_c,t-1)}, \tilde{R}_{P(Z_c,t)})$$

where $\tilde{R}_{ct}$ is the return of the characteristics sorted portfolio c at time t, $\bar{R}_t$ is the equal-weighted average return across the characteristics sorted portfolios, and ψ_c is a complicated coefficient associated with *P(Zc)*. This can be derived from the following assumption about the return-generating process:

$$\tilde{r}_{jt} = \sum_{c=1}^{18} I_{j\in P(Z_c,t-1)} \tilde{R}_{p(Z_c,t)} + \tilde{\varepsilon}_{jt}$$

where $\tilde{r}_{jt}$ is the return of stock j at time t, $I_{j\in P(Z_c,t-1)}$ indicates whether stock *j* belongs to portfolio *P* according to firm characteristics Zc at time *t* –*1*, $\tilde{R}_{p(Z_c,t)}$ *is the return of style portfolio P to which stock j is assigned, and* $\tilde{\varepsilon}_{jt}$ *is stock j*'s firm-specific return component at date t. Since the cross-sectional variance of ex post mean characteristics monthly returns (the first item on the right-hand side of the equation) is only 0.00051, the observed CM profits cannot be explained completely by the cross-sectional dispersion in expected returns proposed by Conrad and Kaul [1998]. The existence of CM profits implies that the second item on the right-hand side is positive.

26 In the construction of ME-BM-DY characteristics partition cells, each stock is given a vector of three coordinates (ScoreME, ScoreBM, and ScoreDY) at any given time to indicate which partition cell the stock is assigned to. For example, large growth stocks with high dividend yield are in favor at the beginning of April 1997. Coincidentally, Stock X with coordinate vector (3, 1, 2) belongs to such an in-favor characteristics portfolio. At a time other than portfolio formation, Stock X may change its characteristics to (1, 3, 1), indicating a small value stock with low dividend yield. The change in firm characteristics for Stock X in this hypothetical case would be 9, which results from the calculation of $(1-3)_2 + (3-1)_2 + (1-2)_2$. By this construction, the change in firm characteristics is bounded by the range of [0, 9]. This indicates the distance between two vectors and thus shows changes in firm characteristics over time relative to the time of portfolio formation.

27 Perez-Quiros and Timmermann [2000] find that small firms are most strongly affected by tighter credit market conditions in a recession. As a result, small firms tend to have high risk sensitivity and expected return over a recession period. Johnson [2002] shows that momentum can be rationalized in a model with stochastic expected growth rates. A momentum sort will tend to sort firms by recent growth rate changes, and, hence, by end- of-period expected return.

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