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Fundamentally, Momentum is Fundamental Momentum
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ABSTRACT

Momentum in firm fundamentals, i.e., earnings momentum, explains the performance of strategies based on price momentum. Earnings surprise measures subsume past performance in cross sectional regressions of returns on firm characteristics, and the time-series performance of price momentum strategies is fully explained by their covariances with earnings momentum strategies. Controlling for earnings surprises when constructing price momentum strategies significantly reduces their performance, without reducing their high volatilities. Controlling for past performance when constructing earnings momentum strategies reduces their volatilities, and eliminates the crashes strongly associated with momentum of all types, without reducing the strategies' high average returns. While past performance does not have independent power predicting the cross section of expected returns, it does predicts stock comovements, and is thus important for explain cross sectional variation in realized returns.

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1. Introduction

Price momentum, i.e., the tendency of stocks that have performed well over the prior year to outperform, going forward, stocks that have performed poorly over the prior year, is often regarded as the most important financial anomaly. The anomaly is observed over long periods and across markets. Momentum has generated large, though highly volatile, returns. The anomaly has been particularly challenging for proponents of market efficiency, as it is difficult to imagine a risk-based story consistent with both the large magnitude and transient nature of momentum returns. It is also problematic for the profession's dominant empirical pricing model, the Fama and French (1993) three factor model, which predicts that momentum, because it covaries negatively with value strategies, should have negative average excess returns. These facts have brought momentum enormous attention in the finance literature. This paper argues that such attention is not deserved. It shows that momentum is not an independent anomaly, but driven by fundamental momentum. That is, price momentum is merely a weak expression of earnings momentum, reflecting the tendency of stocks that have recently announced strong earnings to outperform, going forward, stocks that have recently announced weak earnings.

This may seem surprising, in light of Chan, Jegadeesh, and Lakonishok's (1996, hereafter CJL) well known and widely accepted conclusion that "past return[s] and past earnings surprise[s] each predict large drifts in future returns after controlling for the other" (p. 1681). CJL actually consider the possibility "that the profitability of momentum strategies is entirely due to the component of medium-horizon returns that is related to these earnings-related news," but explicitly reject this hypothesis, concluding that "each momentum variable has separate explanatory power for future returns, so one strategy does not subsume the other" (pp. 1682–3). They draw this conclusion primarily on the basis of return spreads they see in both directions from an independent three by three portfolio sort on past performance and earnings surprises. This is rather weak evidence on which to base their conclusion. These sorts are far too coarse to provide adequate controls for the two variables. In any third of the stock universe picked on the basis of earnings surprises, sorting on past performance still induces significant variation in earnings surprises.

Against this weak test, a preponderance of stronger evidence suggests that earnings momentum drives price momentum. In cross sectional regressions of firms' returns onto past performance and earnings surprises, earnings surprises largely subsume the power of past performance to predict cross sectional variation in expected returns. Adding earnings surprises as an explanatory variable in cross sectional regressions dramatically attenuates the coefficient on past performance, which loses its significance, while adding past performance as an explanatory variable leaves the coefficient on earnings surprises essentially unchanged.

Time-series regressions employing the returns to price and earnings momentum strategies are even more conclusive. These tests are more robust to measurement error than cross sectional regressions, and do not require parametric assumptions regarding the functional form of the relation between expected returns and the predictive variables. These time-series regressions suggest that price momentum is fully captured by earnings momentum. Price momentum strategies do not have a positive alpha relative to earnings momentum strategies, while earnings momentum strategies have large, highly significant alphas relative to price momentum strategies. This suggests that an investor who wants to trade momentum would lose nothing by completely ignored price momentum.

While investors trading earnings momentum would not benefit from trading price momentum, they would benefit from accounting for past performance. Accounting for past performance improves the performance of momentum strategies, if it is used to help investors avoid price momentum when trading earnings momentum. Price momentum contributes to the volatility of earnings momentum strategies, and drives the strategies' largest drawdowns. Earnings momentum strategies explicitly constructed to avoid price momentum consequently have lower volatility, and none of the negative skew, of traditional earnings momentum strategies. Because these earnings momentum strategies unpolluted by price momentum generate average returns comparable to their traditional counterparts, they have significantly higher Sharpe ratios.

The remainder of the paper proceeds as follows. Section 2 establishes the basic asset pricing facts, that earnings surprises subsume the power of past performance to predict returns in both cross sectional and time-series regressions. Section 3 shows that controlling for past performance when constructing earnings momentum strategies improves their performance by decreasing volatility, while controlling for earnings surprises when constructing price momentum strategies hurts their performance by decreasing returns. Section 4 shows that the superior performance of volatility managed price momentum strategies is also explained by earnings momentum. Section 5 shows that the results of this paper are robust to accounting for transaction costs. Section 6 investigates the role of past performance in predicting comovements between stocks. Section 7 concludes.

2. Basic asset pricing results

This section establishes the basic asset pricing facts, that earnings surprises subsume the power of past performance to predict cross sectional variation in expected returns, and that the time-series performance of price momentum strategies is fully explained by the performance of strategies based on earnings surprises. It also shows that these results are robust across the spectrum of firm size.

2.1. Measuring past performance and earnings surprises

Comparing the power of past performance and earnings surprises to predict expected return variation requires measures for each. For past performance I use the measure most commonly associated with price momentum strategies, performance measured over the preceding year, skipping the most recent month to avoid diluting price momentum with short term reversals ($r_{2,12}$). For earnings surprises I use two measures commonly employed in the literature, standardized unexpected earnings (SUE) and cumulative three day abnormal returns (CAR3). SUE is defined as the most recent year-over-year change in earnings per share, scaled by the standard deviation of the these earnings innovations over the last eight announcements, subject to a requirement of at least six observed announcements over the two year window. For earnings per share I use Compustat quarterly data item EPSPXQ (Earnings Per Share (Basic) / Excluding Extraordinary Items). Earnings announcement dates are Compustat quarterly data item RDQ. CAR3 is defined as the cumulative return in excess of that earned by the market over the three days starting the day before the most recent earnings announcement and ending at the end of the day following the announcement.

The time-series average rank correlation between $r_{2,12}$ and SUE is 29.1%, between $r_{2,12}$ and CAR3 is 13.7%, and between SUE and CAR3 is 19.9%. This suggests that the earnings innovations scaled to create standardized unexpected earnings are actually largely expected; SUE correlates more strongly with past performance than it does with the market's contemporaneous reaction to the earnings' announcements. Past performance reflects innovations to investors' beliefs about a firm's prospects, including, but not limited to, guidance the firm has provided regarding it operations, some, but not all of which, are reflected directly in announced earnings. The fact that SUE correlates more strongly with $r_{2,12}$ than with CAR3 indicates that more of the information regarding the change in earnings per share are incorporated into prices prior to announcements than in the days immediately surrounding announcements.

2.2. Fama and MacBeth regressions

Table 1 reports results of Fama and MacBeth (1973) regressions of individual monthly stock returns onto the past performance ($r_{2,12}$), and the most recent earnings surprises measured by both standardized unexpected earnings (SUE) and the cumulative three day abnormal returns (CAR3). Regressions include controls for other variables known to predict cross sectional variation in expected returns, size, relative valuations, profitability, and short horizon past performance, measured here using the log of firms' market capitalizations (ln(ME)), the log of firms' book-to-market ratios (ln(B/M)), gross profitability (GP/A, where GP is revenues minus cost of goods sold and A is assets, as in Novy-Marx (2013)), and stocks' prior month returns ($r_{2,12}$).[1] Independent variables are trimmed at the one and 99% levels. The full sample covers January 1975 through December 2012, with the dates determined by the data requirements for making the SUE and CAR3 strategies. The table also reports subsample results, with the early sample covering January 1975 through December 1993, a period largely coincident with the January 1977 through January 1993 sample studied in CJL, and the late sample covering January 1994 through December 2012.

The first two specifications show the coefficient estimates on past performance and the two earnings surprise measures, respectively, over the entire sample. The first specification shows a significant positive cross sectional correlation between prior year's performance and expected returns, while the second shows far more significant correlations between earnings surprises and expected returns.

The third specification shows that in the regression that includes both past performance and earnings surprises, the coefficient on past performance is reduced by three quarters, and becomes statistically insignificant, while the coefficients on the earnings surprise measures are essentially unmitigated, and become more significant. This suggests that the power past performance has predicting cross sectional variation in expected returns in specification one derives from its correlation with earnings surprises, while the power earnings surprises have to predict returns is unrelated to past performance.

The last four specifications show subsample results consistent with the conclusion that earnings surprises have independent power predicting expected return differences across stocks, while the power of past performance derives primarily from its correlation with earnings surprises.

[1] Chan, Jegadeesh, and Lakonishok (1996) also run Fama and MacBeth regressions of firms' returns on past performance and earnings surprises, but their tests, in addition to covering a much shorter sample, differ from those presented here in at least three important ways. First, for the dependent variable they use stocks' subsequent six month or one year returns, which weakens the tests due to the transient nature of momentum effects. Second, and most importantly, they transform their independent variables into percentile rankings, which reduces the power of the earnings surprise variables. Lastly, they do not include controls for other known cross sectional return predictors.

Table 1. Fama and MacBeth regressions

The table reports results of Fama and MacBeth (1973) regressions of individual monthly stock returns onto past performance, measured over the preceding year skipping the most recent month ($r_{2,12}$), and firms' most recent earnings surprises, measured using both standardized unexpected earnings (SUE) and the cumulative three day abnormal returns around the most recent earnings announcement (CAR3). Regressions include controls for other variables known to predict cross sectional variation in expected returns, the log of firms' market capitalizations (ln(ME)), the log of firms' book-to-market ratios (ln(B/M)), gross profitability (GP/A, where GP is revenues minus cost of goods sold and A is assets), and stocks' prior month returns ($r_{2,12}$). Independent variables are trimmed at the one and 99% levels. The sample covers January 1975 through December 2012, with the dates determined by the data requirements for making the SUE and CAR3 strategies.

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$r_{2,12}$	0.59		0.15	0.80	0.30	0.38	-0.00
	[2.84]		[0.70]	[3.79]	[1.28]	[1.05]	[-0.00]
SUE		0.27	0.26		0.30		0.21
		[17.0]	[19.2]		[16.4]		[11.2]
CAR3		5.84	5.75		6.63		4.87
		[19.7]	[20.4]		[15.2]		[13.9]
ln(ME)	-0.06	-0.08	-0.08	-0.11	-0.13	-0.01	-0.04
	[-1.39]	[-1.69]	[-1.93]	[-1.92]	[-2.11]	[-0.11]	[-0.64]
ln(B/M)	0.44	0.30	0.32	0.46	0.38	0.42	0.27
	[5.96]	[3.82]	[4.47]	[4.94]	[3.93]	[3.65]	[2.47]
GP/A	0.91	0.76	0.75	0.89	0.74	0.93	0.77
	[6.82]	[5.58]	[5.60]	[5.00]	[4.17]	[4.67]	[3.79]
$r_{0,1}$	-4.66	-5.83	-6.00	-6.49	-8.07	-2.83	-3.92
	[-10.2]	[-11.9]	[-12.9]	[-12.1]	[-14.0]	[-3.89]	[-5.53]

2.3. Spanning tests

The results of the Fama and MacBeth regressions shown in Table 1 suggest that the power of past performance to predict cross sectional variation in expected returns is largely subsumed by earnings surprise. This subsection shows that price momentum is fully captured by earnings momentum in time-series regressions.

These time-series regressions, or spanning tests, essentially ask which momentum strategies, among those constructed using past performance and the two measures of earnings surprises, generate significant alpha relative to the others. They do so by regressing the returns of a test strategy, taken from the set of momentum strategies, onto the returns of explanatory strategies, which include the Fama and French factors and the other momentum strategies. Significant abnormal returns suggest an investor already trading the explanatory strategies could realize significant gains by starting to trade the test strategy. Insignificant abnormal returns suggest that the investor has little to gain by starting to trade the test strategy.

For the price momentum strategy I use the up-minus-down factor, UMD, available from Ken French's data library.[2] For the earnings momentum factors I construct analogues to UMD based on the two measures of earnings surprises. Specifically, these factors are constructed from underlying portfolios that are formed monthly, as the intersection of two size and three earnings momentum portfolios. The size portfolios divide stocks into large or small cap universes, based on NYSE median market capitalization. The earnings momentum portfolios divide the world into three portfolios divided at the 30th and 70th percentiles, using NYSE breaks, of earnings surprises, measured using either SUE or CAR3. The earnings momentum factors are each formed as an equal weighted average of value weighted large cap and small cap earnings momentum strategies, which buy the upper tertile and short the bottom tertile of the earnings surprises portfolios based on the corresponding measure of earnings surprises. In a convenient abuse of notation, these earnings momentum factors are denoted SUE and CAR3, the same as the earnings surprise measures on which they are based. The performance of the portfolios underlying these factors is provided in the Appendix, in Table A1.

Figure 1 shows the performance of the three momentum factors, UMD, SUE, and CAR3. The figure shows the growth of a dollar, net of financing costs, invested in the beginning of 1975 into each of the strategies. To facilitate comparison, the strategies are all levered to run at a sample volatility of 10%. The figure shows that both of the earnings momentum strategies dramatically outperformed the price momentum strategy, suggesting

[2] The library resides at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

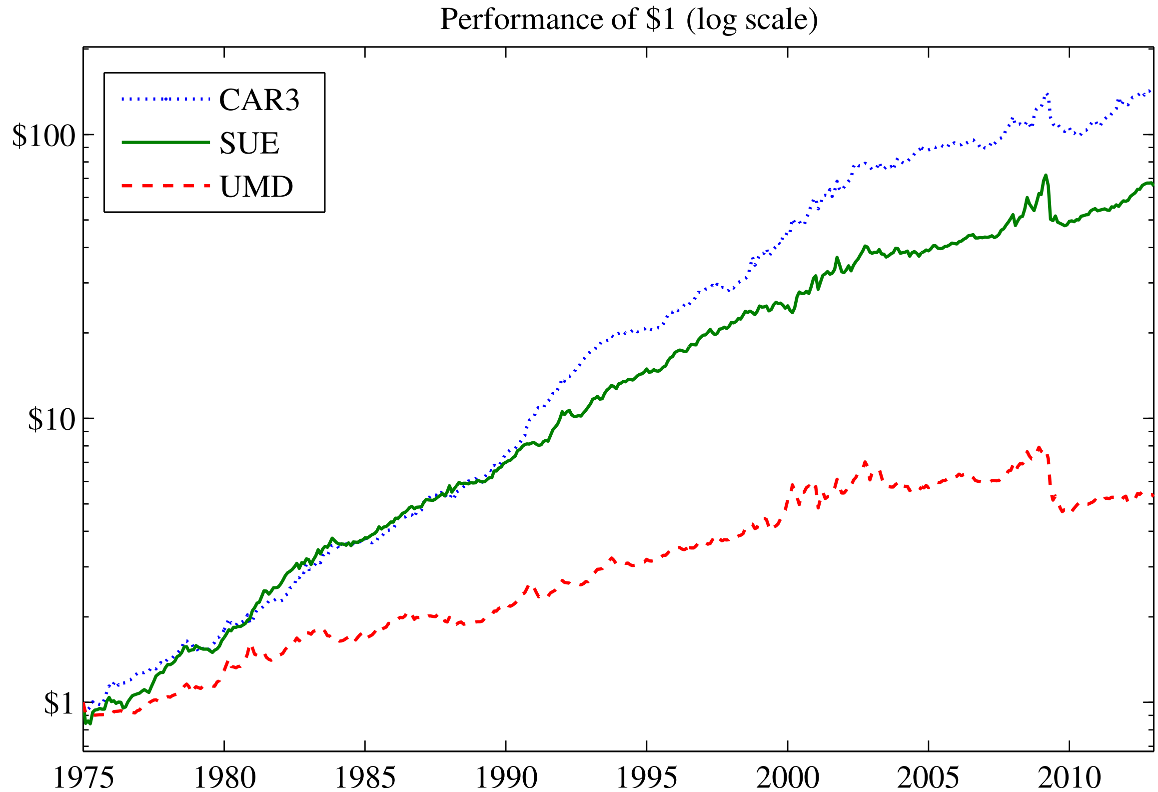

Fig. 1. Comparison of momentum factor performance. The figure shows the value of a dollar invested at the beginning of 1975 in the price momentum factor, UMD (dashed line), and the earnings momentum factors, SUE (solid line) and CAR3 (dotted line). Returns are calculated net of financing costs (i.e., are excess returns). To facilitate comparison, factors are scaled to have a sample volatilities of 10%. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

that these strategies had significantly higher Sharpe rations than UMD.

Table 2 analyzes the performance of the three momentum factors formally. Panel A shows the performance of UMD. Specification one shows that over the 38 year sample the standard price momentum factor earned a highly significant 64 basis points per month, with a t-statistic of 3.03. Specification two provides the standard result that momentum's Fama and French three-factor alpha is even larger. Specification three shows that UMD loads heavily on both SUE and CAR3, and as a result has a significant negative alpha relative to earnings momentum, even after controlling for the three Fama and French factors. This

Table 2
Momentum factor spanning tests
This table presents results of time-series regressions of the form:

$$y_t \quad = \quad \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \varepsilon_t$$

where the y_t are the monthly excess returns to the price momentum factor, UMD, or the earnings momentum factors, SUE and CAR3, and the explanatory factors are the returns to the Fama and French factors (MKT, SMB, and HML), or these factors and the other two momentum factors. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: y = UMD							
α	0.64	0.85	-0.48	0.82	-0.03	0.46	-0.60
	[3.03]	[4.05]	[-2.55]	[3.67]	[-0.13]	[1.29]	[-2.16]
β_{MKT}		-0.18	-0.04		0.08		-0.08
		[-3.83]	[-1.12]		[1.60]		[-1.32]
β_{SMB}		0.07	0.22		0.02		0.33
		[1.07]	[3.87]		[0.24]		[4.05]
β_{HML}		-0.34	-0.17		-0.16		-0.14
		[-4.65]	[-2.96]		[-1.92]		[-1.66]
β_{SUE}			1.18		0.90		1.35
			[10.9]		[6.17]		[8.59]
β_{CAR3}			0.84		0.34		1.03
			[6.09]		[1.82]		[5.18]
adj.-R^2 (%)		5.8	40.6		25.4		50.1
Panel B: y = SUE							
α	0.59	0.70	0.38	0.71	0.41	0.46	0.34
	[7.14]	[8.68]	[5.31]	[7.20]	[4.18]	[3.53]	[3.36]
β_{MKT}		-0.08	-0.03		-0.04		-0.05
		[-4.25]	[-1.94]		[-1.74]		[-2.11]
β_{SMB}		-0.11	-0.11		-0.03		-0.15
		[-3.94]	[-5.21]		[-0.80]		[-5.10]
β_{HML}		-0.10	-0.02		-0.09		0.00
		[-3.44]	[-0.80]		[-2.51]		[0.04]
β_{UMD}			0.18		0.16		0.18
			[10.9]		[6.17]		[8.59]
β_{CAR3}			0.30		0.39		0.22
			[5.52]		[5.03]		[2.91]
adj.-R^2 (%)		8.3	41.4		31.3		49.3

Table 2 continued

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: y = CAR3							
α	0.53	0.59	0.37	0.63	0.39	0.43	0.34
	[8.42]	[9.35]	[6.18]	[8.43]	[4.81]	[4.26]	[3.96]
β_{MKT}		-0.06	-0.02		0.02		-0.05
		[-3.87]	[-1.77]		[1.22]		[-2.62]
β_{SMB}		-0.02	-0.01		-0.04		-0.01
		[-1.08]	[-0.36]		[-1.43]		[-0.26]
β_{HML}		-0.06	-0.01		0.03		-0.03
		[-2.78]	[-0.50]		[1.19]		[-1.23]
β_{UMD}			0.09		0.04		0.10
			[6.09]		[1.82]		[5.18]
β_{SUE}			0.21		0.26		0.16
			[5.52]		[5.03]		[2.91]
adj.-R^2 (%)		3.8	28.2		17.0		35.9

fact, that earnings momentum subsumes price momentum in time-series regressions, drives the success of Hou, Xue, and Zhang's (2014) alternative factor model pricing momentum strategies. Novy-Marx (2015) shows that their model's success pricing portfolios sorted on past performance is driven entirely by post earnings announcement drift in its profitability factor. It also shows that it succeeds in pricing portfolios sorted on gross profitability only by conflating low return earnings profitability, which drives the factor's covariance with gross profitability, with earnings surprises, which drives the factor's high average returns.

Specifications four through seven show consistent subsample results. UMD generated positive returns over both the early and late halves of the sample, though these were only statistically significant over the early sample. Yet even in the early sample, when UMD earned 85 bps/month, it failed to generate abnormal returns relative to the price momentum factors.

Panels B and C show that the earnings factors SUE and CAR3 both fall outside the span of UMD and each other. The earnings momentum strategies both generated highly significant returns over the whole sample, with t-statistics exceeding seven for SUE and eight for CAR3. For both factors the returns are highly significant over both subsamples, though roughly 50% larger and more significant over the early sample. Both earnings momentum factors' returns remain highly significant after controlling for the three Fama and French factors and the other two momentum factors, even in the late sample when their performance was less impressive.

2.4. Results by size

The Fama and MacBeth regression results of Table 1 are primarily identified off of small cap stocks, which account for a large majority of names. The performance of all three of the momentum strategies considered in Table 2 is also driven disproportionately by the small cap stocks, the returns to which are over-weighted when calculating factor returns. These facts raise concerns that the results of the previous subsections are absent from the large cap universe, which accounts for a large majority of market capitalization. This subsection shows that this is not the case. The results also hold among large cap stocks.

Table 3 provides results of spanning tests, similar to those presented in Table 2, performed within NYSE size quintiles. Within each size quintile I construct price and earnings momentum strategies. These buy and sell the top and bottom 30% of stocks within that size quintile on the basis of the corresponding sorting characteristic, $r_{2,12}$, SUE or CAR3. Portfolios are rebalanced monthly, and returns are value weighted.

Panel A of Table 3 reports characteristics of the size portfolios. It gives time-series averages of the number of stocks and average size of stocks in each portfolio, as well as the fraction of the names and market cap in each portfolio.

Panel B shows the performance of the price momentum portfolios constructed within NYSE size quintiles. It shows that sorting on past performance generates positive return spreads across the size portfolios, though these spreads are decreasing monotonically with size. That is, momentum is stronger among smaller stocks. It also shows that except among the smallest stocks, which make up on average only 3.5% of market capitalization, the

Table 3. Spanning tests of value, profitability, and volatility-based defensive strategies, constructed within size deciles

The table reports the performance of price momentum (winner-minus-loser; WML) and earnings momentum (SUE and CAR3) strategies, constructed within each NYSE size quintile. These strategies buy and sell the 30% of stocks with the highest and lowest values of the corresponding sorting characteristic among stocks in the same size quintile. Portfolios are rebalanced monthly, and returns are value-weighted and ignore transaction costs. The table reports the average monthly excess returns to each set of strategies, as well as results of time-series regressions of each set of strategies' excess returns onto the returns of three Fama and French factors and the other two momentum factors constructed within the same size quintile. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Size quintile					
	(1)	(2)	(3)	(4)	(5)	Mean
Panel A: Size portfolio time-series average characteristics						
# of names	3,382	774	503	390	333	
% of names	62.4	14.4	9.4	7.4	6.4	
Firm size, $\$10^6$	6.7	37	87	213	1,553	
% of mkt cap.	3.5	4.4	6.9	13.2	72.0	
Panel B: Momentum strategy average monthly excess returns, by size quintile, and results of $\text{WML}_i = \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{SUE}_i}\text{SUE}_i + \beta_{\text{CAR3}_i}\text{CAR3}_i$						
$E[\text{WML}_i]$	1.43	0.88	0.69	0.47	0.35	0.77
	[5.48]	[3.95]	[3.06]	[1.97]	[1.48]	[3.55]
α	-1.47	-0.13	-0.04	0.08	0.18	-0.28
	[-5.79]	[-0.61]	[-0.20]	[0.41]	[0.83]	
β_{MKT}	-0.24	-0.14	-0.07	-0.11	-0.03	-0.12
	[-5.24]	[-3.32]	[-1.56]	[-2.43]	[-0.63]	
β_{SMB}	0.01	0.29	0.31	0.42	0.30	0.27
	[0.15]	[4.59]	[4.71]	[6.46]	[4.10]	
β_{HML}	-0.09	-0.17	-0.14	-0.36	-0.36	-0.23
	[-1.33]	[-2.72]	[-2.08]	[-5.37]	[-4.79]	
β_{SUE_i}	1.13	1.07	0.71	1.14	0.43	0.90
	[10.8]	[12.2]	[7.72]	[11.4]	[4.48]	
β_{CAR3_i}	1.08	0.34	0.78	0.52	0.55	0.65
	[8.99]	[3.00]	[7.26]	[4.72]	[5.11]	
Adj.-R^2 (%)	49.0	34.5	31.4	37.6	20.0	34.5

Table 3 continued

	Size quintile					
	(1)	(2)	(3)	(4)	(5)	Mean
Panel C: SUE strategy average monthly excess returns, by size quintile, and results of $\text{SUE}_i = \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{WML}_i}\text{WML}_i + \beta_{\text{CAR3}_i}\text{CAR3}_i$						
$E[\text{SUE}_i]$	1.50	0.76	0.53	0.26	0.26	0.66
	[15.6]	[7.17]	[5.21]	[2.75]	[2.46]	[8.59]
α	0.94	0.41	0.44	0.18	0.29	0.45
	[9.84]	[4.23]	[4.61]	[2.23]	[2.83]	
β_{MKT}	0.08	0.02	-0.02	-0.03	-0.11	-0.01
	[4.14]	[1.21]	[-0.98]	[-1.46]	[-4.51]	
β_{SMB}	-0.05	-0.16	-0.17	-0.17	-0.11	-0.13
	[-1.80]	[-5.47]	[-5.42]	[-6.16]	[-3.04]	
β_{HML}	-0.10	-0.03	-0.08	0.05	0.01	-0.03
	[-3.65]	[-1.11]	[-2.32]	[1.60]	[0.33]	
β_{UMD_i}	0.18	0.23	0.16	0.20	0.10	0.17
	[10.8]	[12.2]	[7.72]	[11.4]	[4.48]	
β_{CAR3_i}	0.23	0.25	0.14	0.11	0.16	0.18
	[4.50]	[4.83]	[2.62]	[2.31]	[3.03]	
Adj.-R^2 (%)	39.4	37.0	22.4	31.4	14.2	28.9
Panel D: CAR3 strategy average monthly excess returns, by size quintile, and results of $\text{CAR3}_i = \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{WML}_i}\text{WML}_i + \beta_{\text{SUE}_i}\text{SUE}_i$						
$E[\text{CAR3}_i]$	1.29	0.76	0.46	0.32	0.20	0.61
	[14.8]	[9.41]	[5.22]	[3.77]	[2.12]	[10.8]
α	0.79	0.60	0.35	0.28	0.15	0.43
	[9.03]	[7.29]	[4.17]	[3.36]	[1.66]	
β_{MKT}	-0.03	-0.03	-0.03	-0.04	-0.02	-0.03
	[-2.01]	[-1.63]	[-1.78]	[-1.90]	[-1.14]	
β_{SMB}	-0.02	-0.06	0.04	-0.00	0.03	-0.00
	[-1.02]	[-2.30]	[1.30]	[-0.14]	[0.95]	
β_{HML}	0.11	0.01	-0.08	-0.02	-0.04	-0.00
	[4.57]	[0.40]	[-2.88]	[-0.69]	[-1.34]	
β_{UMD_i}	0.14	0.06	0.13	0.09	0.10	0.10
	[8.99]	[3.00]	[7.26]	[4.72]	[5.11]	
β_{SUE_i}	0.19	0.20	0.11	0.11	0.13	0.14
	[4.50]	[4.83]	[2.62]	[2.31]	[3.03]	
Adj.-R^2 (%)	39.4	16.3	21.8	12.2	11.0	20.1

returns to the momentum strategies are completely insignificant relative to the earnings momentum strategies constructed within the same size quintiles, even after controlling for the Fama and French factors. Among the smallest stocks, where past performance generates by far the largest spread return, the price momentum strategy has a large, highly significant, negative alpha with respect to the earnings momentum strategies.

Panels C and D show that both earnings surprise measures generate returns spreads in each size quintile that are more significant than those generated by sorting on past performance. They also show that all ten of the earnings momentum strategies generated positive alphas relative to the Fama and French factors and the other momentum strategies constructed within the same size quintiles. These alphas are all significant at the 5% level, except for the CAR3 strategy constructed using stocks with the largest capitalizations, for which the alpha is significant only at the 10% level.

3 Conditional strategies

Past performance and earnings surprises, especially surprises measured by SUE, are positively correlated. Sorting on past performance consequently yields systematic variation in SUE across portfolios, while sorting on SUE yields systematic variation in past performance across portfolios. This conflation makes it difficult to evaluate the impact of the two effects independently. This section attempts to address this issue by constructing momentum strategies that are neutral with respect to SUE, and SUE strategies that are neutral with respect to past performance.

These strategies are constructed by controlling for one variable while sorting on the other. Specifically, stocks are first matched on the control variable, and then assigned to portfolios on the basis of the primary sorting variable. For example, a strategy that selected pairs of stocks most closely matched on SUE, and then for each pair bought the one with stronger past performance and shorted the one with weaker past performance, would have substantial variation in past performance, but essentially none in recent earnings surprises.

To make the conditional strategies, UMD|SUE ("UMD conditional on SUE") and SUE$|r_{2,12}$ ("SUE conditional on prior year's performance"), as directly comparable as possible to UMD and SUE, I would like them to have the same variation in the primary sorting characteristic as their traditional counterparts. That is, I would like a past performance spread in UMD|SUE similar to that in UMD, and an earnings surprise spread in SUE$|r_{2,12}$ similar to that in SUE. UMD and SUE hold the 30% of stocks with the highest past performance or earnings surprise rankings, and short the 30% with the lowest rankings, so the average ranking of the primary sorting variable on the long and short sides of UMD and SUE are 85% and 15%, respectively.

If past performance and earnings surprises were uncorrelated, then selecting groups of stocks matched on the control variable would not affect the distribution of the rankings on the primary sorting characteristic. The stocks' rankings on the primary sorting characteristic would then be like n independent draws of a standard uniform variable. The maximal order statistic of n independent standard uniform variables is distributed nx^{n-1}, so has an expected value of $\int_0^1 x(nx^{n-1}dx) = n/(n+1)$. The expected value of the minimal order statistic is, by symmetry, $1/(n+1)$. So if past performance and earnings surprises were uncorrelated, then assigning stocks on the basis of the primary sorting variable among groups of $n = 6$ stocks matched on the control variable would yield expected average rankings of the primary sorting variable in the high and low portfolios of $6/7 = 85.3\%$ $1/7 = 15.3\%$, respectively, similar to those obtained from a univariate tertile sort.

Past performance and earnings surprises are significantly correlated, however, which is what conflates price and earnings momentum strategies in the first place. This correlation reduces the spread in the primary sorting characteristic between the high and low portfolios of the conditional strategies. Groups of n stocks matched on one of the characteristics exhibit less variation in the other characteristics, because of the correlation, than would n randomly selected stocks. Variation in the primary sorting characteristic among stocks matched on the control variable comes only from the variation in the former unexplained by the latter. To achieve a spread in the primary sorting characteristic for the conditional strategies comparable to that observed in the traditional price and earnings momentum strategies consequently requires initially selecting larger groups of matched stocks. Selecting groups of seven stocks matched on the control variable yields conditional strategies with variation in the primary sorting characteristic that most closely matches the variation resulting from the univariate tertile sorts.

Finally, to make these conditional strategies as comparable to UMD and SUE as possible, the returns to the conditional strategies are also averaged across large and small cap strategies. Specifically, large and small cap stocks, defined as those with above and below NYSE median market capitalizations, are matched into groups of seven on the basis of either past performance ($r_{2,12}$) or recent earnings surprises (SUE). Stocks are then assigned to portfolios on the basis of their rankings on the other variable, earnings surprises or past performance. The conditional earnings surprise factor, SUE$|r_{2,12}$, and the conditional momentum factor, UMD|SUE, are an equal-weighted average of the value-weighted large and small cap strategies that hold the corresponding high portfolios and short the corresponding low portfolios.[3]

Figure 2 shows the time-series average of the average past performance and earnings surprise ranks of the portfolios underlying the conditional momentum and earnings surprise factors, as well as the unconditional factors UMD and SUE. Panel A shows past performance ranks. The UMD portfolios and UMD|SUE exhibit nearly identical variation in past performance ranks. The unconditional SUE factor exhibits about a third of this variation, despite being constructed without consideration for past performance. The conditional earnings surprise factors exhibit essentially no variation in past performance rankings, as intended.

Panel B shows similar results for earnings surprise ranks. The unconditional SUE factor and SUE$|r_{2,12}$ exhibit almost indistinguishable levels of earnings surprise rank variation,

[3]The appendix also reports results for conditional strategies constructed by selecting only matched triples on the conditioning variable. This yields similar name diversification to UMD and SUE on the long and short sides, but significantly less variation in the primary sorting characteristic between the high and low portfolios. Results using this alternative methodology for conditional factor construction are consistent with those presented here.

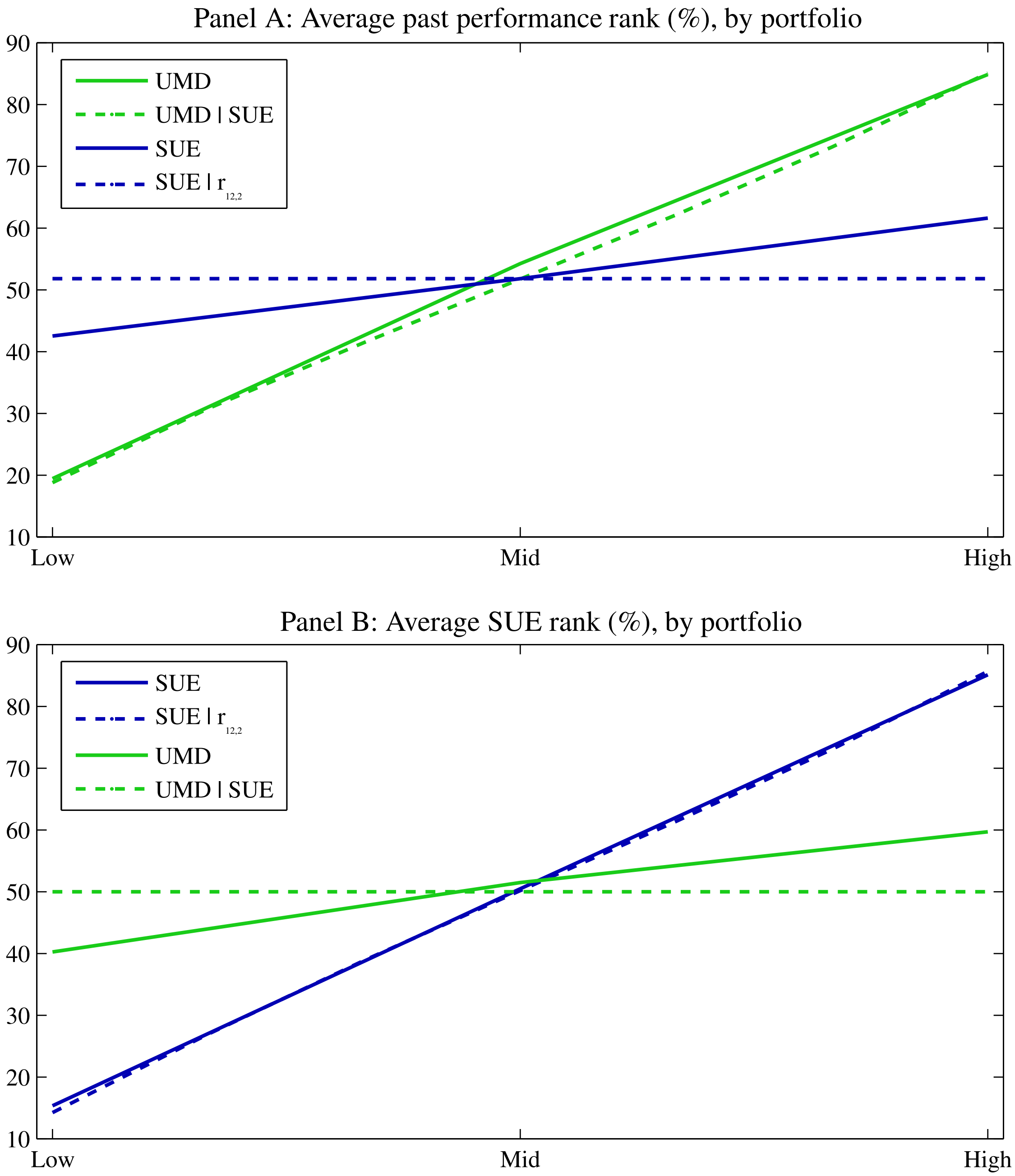

Fig. 2. Portfolio average past performance and earnings surprise ranks. The figure shows the time-series average of the average $r_{2,12}$ (Panel A) and SUE (Panel B) of the portfolios underlying the unconditional price and earnings momentum strategies (UMD and SUE) and the conditional price and earnings momentum strategies (UMD|SUE and SUE|$r_{2,12}$). These are tertile sorted on $r_{2,12}$ and SUE (unconditional strategies), or sorted into seven portfolios on one of these variables from among groups most closely matched on the other (conditional strategies). The sample covers January 1975 through December 2012.

UMD shows somewhat less than one third this variation, and the conditional momentum factor essentially no variation, in earnings surprise ranks.

Figure 3 shows the performance over time of the four strategies, UMD, UMD|SUE, SUE, and SUE|$r_{2,12}$. The figure shows the growth of a dollar, net of financing costs, invested in the beginning of 1975 into each of the strategies, where the strategies are all levered to run at an ex post volatility of 10%. The figure shows that purging price momentum from the earnings momentum strategy improves its performance. It also eliminates the large drawdown that the unconditional SUE strategy experienced during

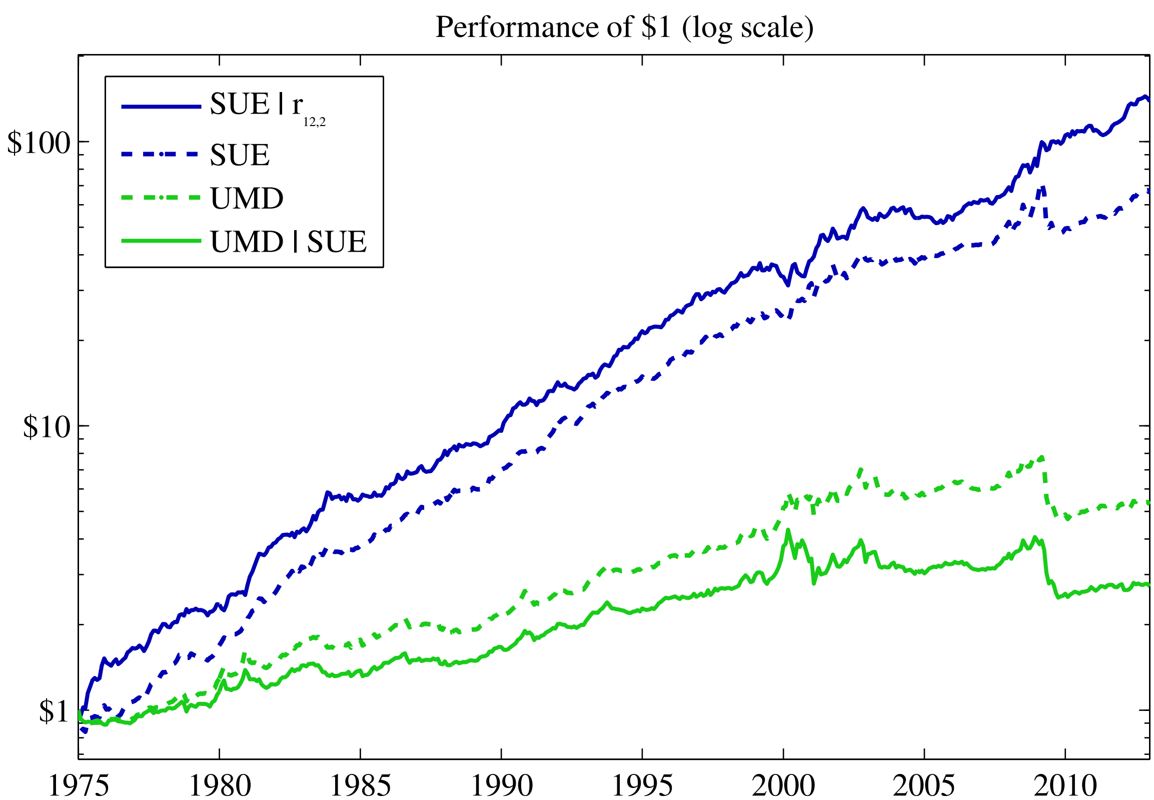

Fig. 3. Comparison of conditional and unconditional price and earnings momentum strategies. The figure shows the value of a dollar invested at the beginning of 1975 in UMD (light dashed line), the SUE factor (dark dashed line), the price momentum factor constructed to be neutral with respect to earnings momentum (UMD|SUE; solid light line), and the earnings momentum factor constructed to be neutral with respect to price momentum (SUE|$r_{2,12}$; solid dark line). Returns are calculated net of financing costs (i.e., are excess returns). To facilitate comparison, factors are scaled to have a sample volatilities of 10%. The sample covers January 1975 through December 2012.

the momentum crash in the spring of 2009. The figure shows that purging earnings momentum from UMD, however, yields a significant worsening in the performance of the price momentum strategy.

Table 4 analyzes the performance of the four strategies formally. The first specification shows that UMD generated highly significant gross spreads over the 38 year sample. The second shows that UMD has a significant information ratio relative to the momentum factor constructed to be neutral with respect to earnings surprises, UMD|SUE, suggesting earnings momentum significantly contributes to the performance of the standard price momentum factor. The third specification shows that UMD loads heavily on both the conditional factors UMD|SUE and SUE|$r_{2,12}$, and that these loadings explain UMD's performance. UMD's loading on the conditional earnings momentum factor is roughly a third of its loadings on the conditional price momentum factor, consistent with the UMD portfolios' earnings surprise rank spread one third as large as their past performance rank spread, observed in Figure 2.

Specifications four through six show that the unconditional earnings momentum factor SUE generated a spread similar to, but much more significant than, that on UMD. They also show that SUE, like UMD, loads heavily on both the conditional factors, and that these loadings also explain SUE's performance. SUE's loading on the conditional price momentum factor is roughly a quarter of its loadings on the conditional earnings momentum factor, again consistent with the relative earnings surprise and past performance rank spreads observed on the factors' underlying portfolios in Figure 2.

Specification seven shows that UMD|SUE, the price momentum factor purged of earnings momentum, generated only two-thirds the spread of the standard UMD factor, and that this spread is significant at the 10% level, but not at the 5% level. Specification eight shows that UMD|SUE has a significant negative alpha relative to UMD, while specification nine shows that this negative alpha is insignificant after controlling for the short position UMD|SUE takes in SUE after controlling for UMD.

Specifications ten through twelve show that SUE|$r_{2,12}$, the earnings momentum

Table 4
Conditional price and earnings momentum strategy performance

This table presents results of time-series regressions of the form:

$$y_t \quad = \quad \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \varepsilon_t$$

where the y_t are the monthly excess returns to either UMD (specifications one to three), the earnings momentum factor SUE (specifications four to six), the price momentum factor constructed to be neutral with respect to earnings momentum UMD|SUE (specifications seven to nine), and the earnings momentum factor constructed to be neutral with respect to price momentum SUE|$r_{2,12}$ (specifications ten to twelve). The conditional factors are constructed similar to UMD, but sort stocks on the primary sorting characteristic ($r_{2,12}$ or SUE) from among stocks matched on the other characteristic. The initial match selects groups of seven stocks, which yields variation in the primary sorting characteristic nearly identical to that obtained from a univariate tertile sort. Explanatory factors are taken from the same set of strategies. The sample covers January 1975 through December 2012.

	dependent variable											
	y = UMD			y = SUE			y = UMD|SUE			y = SUE|$r_{2,12}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	0.64	0.25	0.09	0.59	0.13	0.04	0.45	-0.23	-0.07	0.58	0.25	0.22
	[3.03]	[3.95]	[1.38]	[7.14]	[1.97]	[0.86]	[1.93]	[-3.18]	[-0.99]	[8.42]	[4.68]	[4.74]
$\beta_{\text{UMD\|SUE}}$		0.86	0.86			0.17						
		[68.1]	[71.4]			[17.4]						
$\beta_{\text{SUE}\|r_{2,12}}$			0.28		0.79	0.81						
			[6.68]		[18.6]	[24.6]						
β_{UMD}								1.06	1.14			-0.15
								[68.1]	[64.0]			[-12.4]
β_{SUE}									-0.35		0.55	0.76
									[-7.64]		[18.6]	[24.8]
adj.-R^2 (%)		91.1	91.8		43.2	65.9		91.1	92.1		43.2	57.6

constructed to be neutral with respect to past performance, generated a similar, even more significant, spread to that observed on the unconditional factor SUE, and that it has an extremely large information ratio relative both to SUE and to SUE and UMD.

None of the inferences discussed here change if one includes controls for the three Fama and French factors in the time-series regressions. The results are also even stronger if the conditional strategies are constructed such that the underlying portfolios have similar name diversification, as opposed to primary sorting characteristic variation, to the portfolios underlying UMD and SUE (results provided in Table A2, in the appendix).

Price momentum strategies are also known to exhibit large negative skew and significant excess kurtosis, i.e., they generate extreme moves more frequently than if the returns were log-normally distributed, and these extreme moves are more likely to be crashes. Table 5 demonstrates that these features of momentum strategy performance are driven by price, not earnings, momentum. While the table shows that earnings momentum strategy also exhibits large negative skew and significant excess kurtosis, the earnings momentum strategy constructed controlling for price momentum has positive skew and only mild excess kurtosis.

Table 5
Higher moments of momentum strategy performance

This table gives the higher moments and drawdown performance of the unconditional price and earnings momentum strategies, UMD and SUE, the price momentum strategy constructed to be neutral with respect to earnings momentum, UMD|SUE, and SUE$|r_{2,12}$ and the earnings momentum strategy constructed to be neutral with respect to price momentum. Results for the market are provided for comparison. The sample covers January 1975 through December 2012.

	MKT	UMD	SUE	UMD|SUE	SUE$\|r_{2,12}$
Volatility (%)	15.8	15.6	6.1	17.3	5.1
Skewness	-0.64	-1.50	-1.74	-1.05	0.46
Excess kurtosis	2.10	11.4	15.0	8.37	0.96
Max loss % (nat. vol.)	54.3	57.6	21.4	67.3	8.7
Max loss % (10% vol.)	37.2	40.7	33.7	42.3	16.6
Sharpe ratio	0.48	0.49	1.16	0.32	1.35

4. Constant volatility strategies

The negative skew and excess kurtosis in price momentum strategies are also analyzed in detail by both Barroso and Santa-Clara (2013) and Daniel and Moskowitz (2014). These papers argue that momentum's crash risk is time-varying and predictable, and that managing crash risk significantly improves momentum strategy performance, making momentum even more difficult to explain. This section shows that fundamental momentum explains even these high Sharpe ratio, risk-managed, price momentum strategies.

To construct the risk-managed momentum strategies I follow Barroso and Santa-Clara (2013), who lever a winners-minus-losers strategy each month attempting to hit a target volatility, i.e., they scale a standard momentum strategy by its trailing volatility.[4] I construct the constant volatility strategies UMD*, SUE*, and CAR3* similarly, levering each corresponding dollar long/dollar short strategy by an amount that is inversely proportional to that strategy's realized daily volatility over the preceding month. To facilitate comparison between the constant volatility strategies and the dollar long/dollar short strategies, the target volatility is picked such that the average leverage employed in each of the constant volatility strategies is close to one.

Figure 4 shows the trailing 12-month average leverage for each strategy. The figure also includes, for comparison, the leverage for a similarly constructed constant volatility market factor, MKT*. The strategies exhibit similar leverage at each point in time. For example, all the strategies show dramatic reductions in leverage during the NASDAQ deflation, roughly coincident with the terrorist attacks of 9/11/2001, and following the start of the great recession after 2008, both times of market stress and high uncertainty. While Barroso and Santa-Clara (2013) claim in their abstract that "the major source of predictability is not time-varying market risk but rather momentum-specific risk," the figure suggests that

[4] Daniel and Moskowitz (2014) employ a similar procedure, but also incorporate information regarding their estimation of momentum's conditional expected returns, based on their observation that momentum has performed poorly when its volatility has been high in periods after the market has performed poorly. While generated stronger results, their procedure is more complicated. It also employs fitted returns based on parameters estimated over the whole sample, raising look-ahead bias concerns.

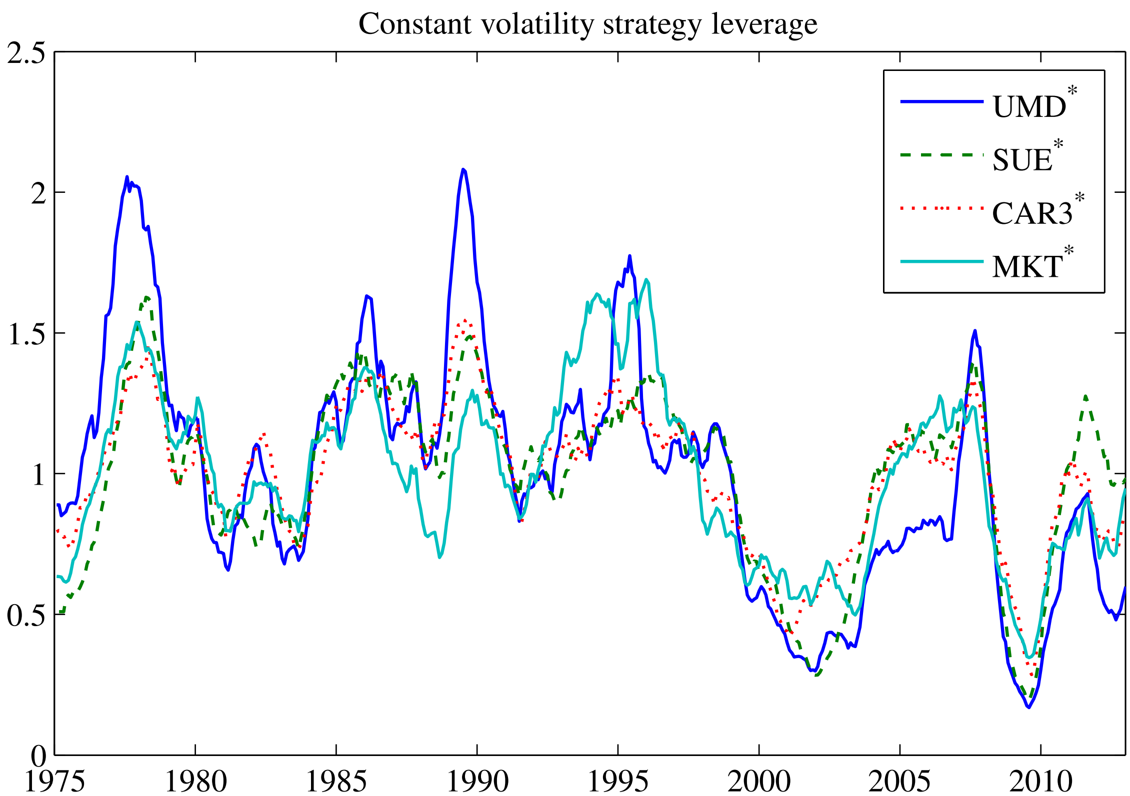

Fig. 4. Constant volatility strategy leverage. The figure shows the leverage employed each month to construct the constant volatility strategies UMD*, SUE*, and CAR3*. This leverage is inversely proportional to the dollar long/dollar short strategies' realized daily volatility over the preceding month. The target volatility is picked such that the average leverage for each of the constant volatility strategies is close to one. Leverage for a similarly constructed constant volatility market strategy, MKT*, is provided for comparison. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

the volatility of momentum strategies is actually related to the level of general market uncertainty.

Figure 5 shows the performance over time of the three constant volatility momentum strategies, UMD*, SUE*, and CAR3*, and includes the conventional momentum factor UMD for comparison. The figure shows the growth of a dollar, net of financing costs, invested in the beginning of 1975 into each of the strategies, where to facilitate comparison the strategies are all levered to run at an average sample volatility of 10%. Consistent

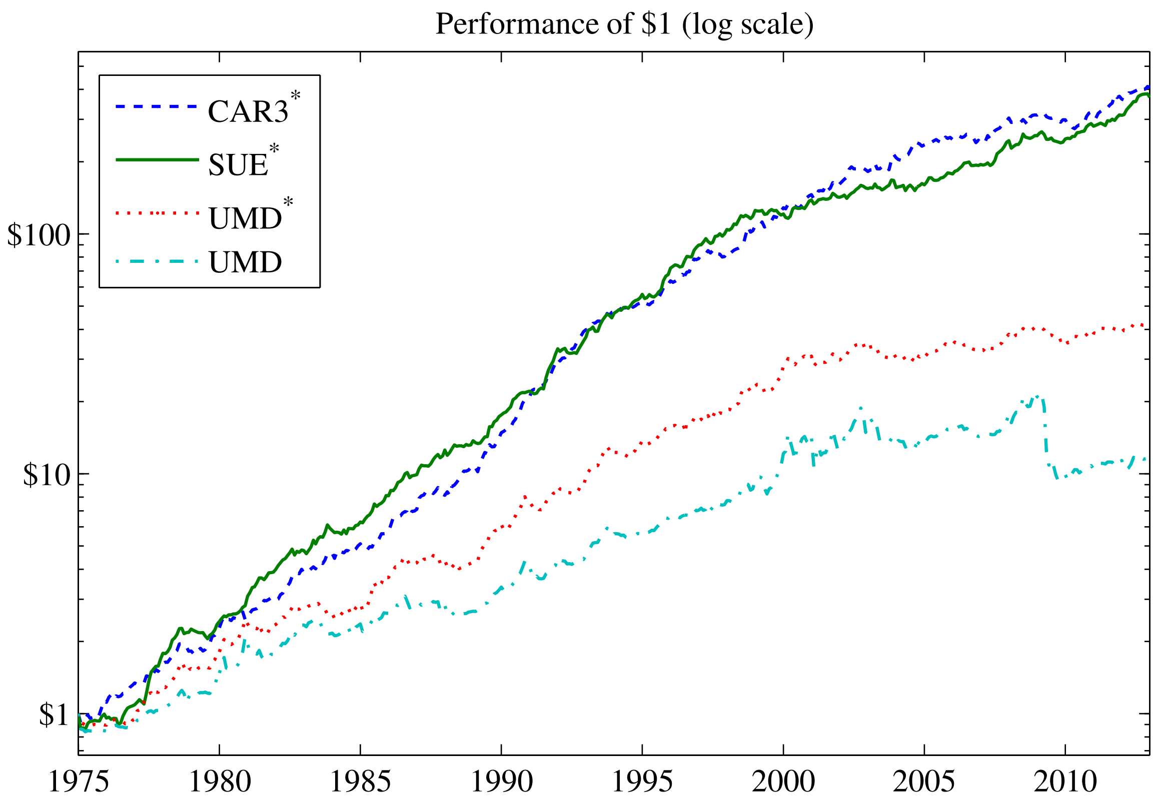

Fig. 5. Constant volatility strategy performance. The figure shows the value of a dollar invested at the beginning of 1975 in the constant volatility price momentum factor, UMD* (dotted line), and the constant volatility earnings momentum factors, SUE* (solid line) and CAR3* (dashed line). The performance of the conventional momentum factor, UMD (dot-dashed line), is provided as a benchmark. Returns are calculated net of financing costs (i.e., are excess returns). To facilitate comparison, factors are scaled to have a sample volatilities of 10%. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

with Barroso and Santa-Clara (2013) and Daniel and Moskowitz (2014), the figure shows that the constant volatility price momentum strategy, UMD*, generates far superior performance to its conventional counterpart, and mostly avoids the momentum crash in the spring of 2009. The figure also shows, however, that the constant volatility earnings momentum strategies dramatically outperform the constant volatility price momentum strategy.

Table 6 formally analyzes the performance of the constant volatility strategies. Panel A investigates the performance of UMD*. Specification one shows that over the 38 year sample the constant volatility price momentum strategy earned 85 basis points per month, with a t-statistic twice as large as that on the average excess return to the conventional momentum factor (6.34 versus 3.03). Specification two shows that UMD* also has a large, highly significant information ratio relative to conventional momentum. UMD* had an alpha of 47 bps/month relative to UMD and the three Fama and French factors. The t-statistic on this alpha is 5.65, implying an extremely high information ratio. Specification three shows that UMD* is inside the span of the constant volatility earnings momentum factors. UMD* had a completely insignificant alpha of 2 bps/month relative to SUE*, CAR3*, and the three Fama and French factors.

Specifications four through seven show consistent subsample results. UMD* generated highly significant returns, even over the late half of the sample when UMD failed to do so, though the strategy did, similar to UMD, deliver average returns roughly twice as high over the early sample. In both subsamples, however, this performance is entirely explained by the strategy's loadings on the constant volatility earnings momentum factors.

Panels B and C show that the constant volatility earnings factors SUE* and CAR3* are both outside the span of UMD* and each other. The earnings momentum strategies both generated highly significant returns over the whole sample, with t-statistics close to ten. These returns are highly significant over both subsamples, though again more impressive over the early sample. These returns are essentially unmitigated after controlling for the three Fama and French factors and UMD, and remain highly significant after controlling for the three Fama and French factors and the other two constant volatility momentum factors.

Table 6
Constant volatility strategy performance

This table presents results of time-series regressions of the form:

$$y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \varepsilon_t$$

where the y_t are the monthly excess returns to the constant volatility price momentum factor, UMD*, or the constant volatility earnings momentum factors, SUE* and CAR3*, and the explanatory factors are the returns to the Fama and French factors (MKT, SMB, and HML), or these factors and the other two constant volatility momentum factors. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: y = UMD*							
α	0.85	0.47	0.02	1.15	0.14	0.56	-0.07
	[6.34]	[5.65]	[0.18]	[5.49]	[0.58]	[3.33]	[-0.43]
β_{MKT}		0.09	0.01		0.06		-0.02
		[4.69]	[0.35]		[1.26]		[-0.68]
β_{SMB}		-0.05	0.05		0.01		0.07
		[-1.75]	[1.36]		[0.14]		[1.61]
β_{HML}		0.03	-0.09		-0.05		-0.11
		[0.95]	[-2.24]		[-0.66]		[-2.46]
β_{UMD}		0.53					
		[28.9]					
β_{SUE^*}			0.86		0.82		0.96
			[9.23]		[5.96]		[7.24]
β_{CAR3^*}			0.57		0.49		0.61
			[5.33]		[2.89]		[4.48]
adj.-R^2 (%)		65.5	28.0		23.5		32.8
Panel B: y = SUE*							
α	0.62	0.56	0.36	0.80	0.47	0.43	0.28
	[9.96]	[9.40]	[5.84]	[8.20]	[4.56]	[5.82]	[4.02]
β_{MKT}		0.01	-0.01		-0.02		-0.01
		[0.82]	[-0.41]		[-1.03]		[-0.56]
β_{SMB}		-0.06	-0.05		-0.01		-0.05
		[-3.21]	[-2.53]		[-0.42]		[-2.51]
β_{HML}		-0.01	-0.01		-0.09		0.03
		[-0.46]	[-0.73]		[-2.64]		[1.21]
β_{UMD}		0.12					
		[8.86]					
β_{UMD^*}			0.18		0.17		0.20
			[9.23]		[5.96]		[7.24]
β_{CAR3^*}			0.23		0.29		0.13
			[4.58]		[3.86]		[2.00]
adj.-R^2 (%)		16.0	26.9		26.8		28.1

Table 6 continued

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: y = CAR3*							
α	0.54	0.50	0.35	0.69	0.43	0.39	0.28
	[10.1]	[9.42]	[6.22]	[8.86]	[4.91]	[5.42]	[3.88]
β_{MKT}		0.00	-0.01		0.02		-0.03
		[0.02]	[-1.09]		[1.03]		[-2.29]
β_{SMB}		-0.03	-0.02		-0.05		-0.01
		[-1.94]	[-0.95]		[-1.63]		[-0.37]
β_{HML}		-0.00	-0.00		0.02		-0.01
		[-0.08]	[-0.28]		[0.61]		[-0.51]
β_{UMD}		0.08					
		[7.24]					
β_{UMD^*}			0.10		0.07		0.14
			[5.33]		[2.89]		[4.48]
β_{SUE^*}			0.19		0.22		0.14
			[4.58]		[3.86]		[2.00]
adj.-R^2 (%)		10.7	17.3		15.7		18.6

5 Transaction costs

Before getting overly excited about the remarkable performance of the momentum strategies observed in the preceding sections, it must be remembered that trading momentum entails significant transaction costs, costs which have, up until now, been ignored. Both the long and short sides of conventional SUE factor turn over, on average, more than twice a year. This costs on average 35 bps/month to trade.[5] The UMD and CAR3 factors are even more expensive to trade, turning over on average three times per year at an average cost of 50 bps/month. These costs are sufficient to wipe out most of the strategies' excess returns.

[5]Transaction cost estimates are all made using the methodology of Novy-Marx and Velikov (2014). This methodology employs Hasbrouck's (2009) Bayesian-Gibbs sampling procedure to estimate effective spreads using a generalized version of the Roll (1984) model, where sufficient data is available, and a nearest matching algorithm on size and volatility where it is not. The procedure yields estimates of the effective spreads faced by a small liquidity demander, and thus represent a conservative estimate for small traders without significant market impact. The estimates ignore the convexity in price impact from large trades, and may thus understate the costs faced by traders with significant market footprints.

The constant volatility factors generate superior performance, but are even more costly to trade. Changing the strategies' leverage each month induces significant additional turnover. The constant volatility earnings momentum strategies' leverage on the dollar long/dollar short strategies changes on average by almost 25 percentage points per month. The average leverage adjustment for the constant volatility price momentum strategy is slightly higher. These leverage adjustments result in an additional 25% average one-way transactions each month on each side of the strategies, increasing the cost of trading by roughly another 25 bps/month. These higher costs are again sufficient to eat up most of the constant volatility strategies' superior gross returns.

The strategies considered so far, however, have all been constructed without regard for transaction costs. Consciously designing momentum strategies to minimize transaction costs yields strategies with significantly better net performance, though this performance is still obviously significantly worse than what could have been achieved if trading were costless. Novy-Marx and Velikov (2014) find that the single most effective trading cost mitigation technique is to trade using a buy/hold spread, i.e., to have a more stringent requirement for actively trading into a position than for maintaining an open position. The buy/hold spread eliminates much of the trading that results from stocks entering a portfolio one month only to fall out the next, a type of transaction that represents a significant fraction of turnover with standard academic portfolio construction.

When constructing strategies that account for transaction costs I consequently follow Novy-Marx and Velikov (2014), who find that a buy/hold spread of 20% yields significant trading costs reductions while maintaining a similar exposure to the sorting characteristic. Specifically, stocks enter the long portfolio when they enter the top quintile of the sorting characteristic using NYSE breaks, and remain in this portfolio as long as they remain in the top two quintiles. Similarly, on the short side, stocks are sold when they enter the bottom quintile of the sorting characteristic using NYSE breaks, and are covered only when they fall out of the bottom two quintiles. The strategies, like UMD, are constructed as an equal weighted average of the value weighted large and small cap strategies, where large and small stocks are defined as those with above and below NYSE median market capitalization. To further reduce turnover and transaction costs, reclassification from large to small, or small to large, does not force the closing of open positions. Using this buy/hold spread yields a nearly 50% reduction in turnover and transaction costs for the price momentum strategy, and significant but more modest reductions for the SUE and CAR3 strategies of roughly one third and one quarter, respectively.

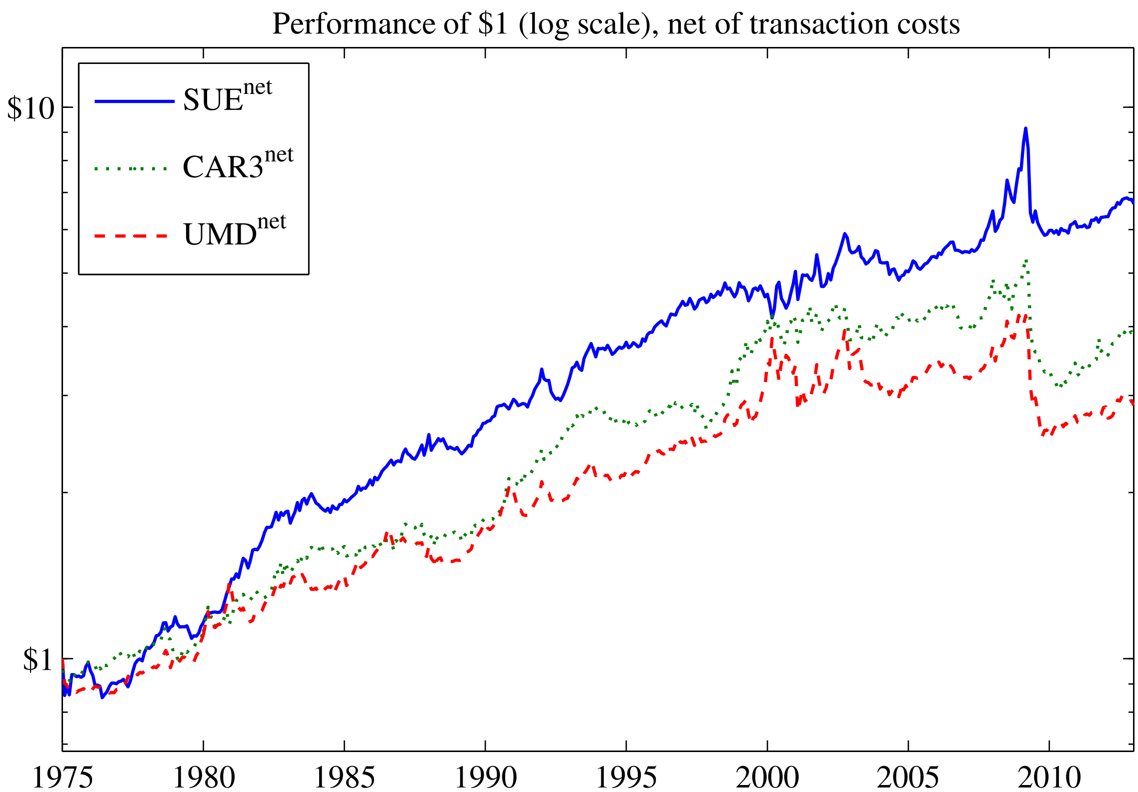

Fig. 6. Comparison of momentum factors net of transaction costs. The figure shows the value of a dollar, net of financing costs, invested at the end of the first quarter of 1974 in the ROE factor, rebalanced monthly on the basis of the most recently announced quarterly earnings-to-book, and similarly constructed factors based on standardized unexpected earnings (PEAD), earnings innovations-to-book (ΔROE), lagged earnings-to-book (lag-ROE), and a lower frequency earnings-to-book strategy based on annual return-on-equity, which is only rebalanced once a year, at the end of June (E/B). Returns are calculated net of financing costs (i.e., are excess returns). To facilitate comparison, factors are scaled to have a sample volatilities of 10%. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

Figure 6 shows the performance, net of transaction costs, of the three momentum factors constructed using the buy/hold spread, UMD^{net}, SUE^{net}, and $CAR3^{net}$. The figure shows the growth of a dollar, net of financing costs, invested in the beginning of 1975 into each of the strategies, where to facilitate comparison the strategies are all levered to run at an average sample volatility of 10%. The figure shows that the strategies all generate positive abnormal returns, even after accounting for transaction costs, though this performance is severely attenuated relative to that calculated ignoring transaction costs. Consistent with earlier results, the earnings momentum strategies generate superior performance to the price momentum strategy.

Table 7 replicates the spanning tests of Table 2, using the transaction cost mitigated strategies' net returns. Panel A shows that price momentum delivered significant returns even after accounting for transaction costs, though accounting for transaction costs reduced the momentum strategy's Sharpe ratio by a third and makes its returns only marginally significant. It also shows that the earnings momentum factors do an exceptional job pricing the price momentum factor. The price momentum factors' net alpha relative to the Fama and French factors and the net earnings momentum factors is only one basis point per month, and completely insignificant. This result is consistent with that observed in Table 2. That table showed a significant negative alpha on price momentum relative to the two earnings momentum factor, but the price momentum tracking portfolio took large positions in both earnings momentum factors, and incurring transaction costs on both these positions was more expensive to trade. After accounting for trading costs the price momentum factor and its tracking portfolio generate similar returns.

While price momentum's net performance is inside the span of the net earnings momentum factors, Panel B shows that SUE^{net} is outside the span of UMD^{net} and $CAR3^{net}$. SUE^{net} earned highly significant returns over the sample (test-statistic of 3.40) even after accounting for transaction costs, and had a highly significant alpha relative to the three Fama and French factors and the other two momentum factors. This net performance was positive, but not statistically significant, over the late half of the sample, covering 19 years.

Table 7
Momentum strategy performance accounting for transaction costs

This table presents results of time-series regressions of the form:

$$y_t \quad = \quad \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \varepsilon_t$$

where the y_t are the monthly excess returns, net of transaction costs, to the price momentum factor, UMD^{net}, or the earnings momentum factors, SUE^{net} and CAR3^{net}, where these strategies are constructed using a buy/hold spread to reduce turnover and transaction costs, and the explanatory factors are the returns to the Fama and French factors (MKT, SMB, and HML), or these factors and the other two net return momentum factors. The sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: $y = \text{UMD}^{\text{net}}$							
α	0.45	0.71	0.01	0.59	0.08	0.30	-0.00
	[2.03]	[3.25]	[0.03]	[2.55]	[0.40]	[0.80]	[-0.02]
β_{MKT}		-0.18	-0.03		0.06		-0.06
		[-3.66]	[-0.66]		[1.34]		[-0.92]
β_{SMB}		0.02	0.17		-0.01		0.26
		[0.23]	[2.92]		[-0.15]		[3.01]
β_{HML}		-0.42	-0.21		-0.15		-0.24
		[-5.67]	[-3.57]		[-1.82]		[-2.60]
$\beta_{\text{SUE}^{\text{net}}}$			0.96		0.78		1.09
			[9.77]		[5.93]		[7.24]
$\beta_{\text{CAR3}^{\text{net}}}$			0.91		0.76		0.90
			[7.79]		[4.74]		[5.24]
adj.-R^2 (%)		7.2	43.3		34.5		47.6
Panel B: $y = \text{SUE}^{\text{net}}$							
α	0.32	0.46	0.24	0.42	0.33	0.22	0.19
	[3.40]	[4.96]	[3.22]	[3.78]	[3.39]	[1.47]	[1.75]
β_{MKT}		-0.09	-0.04		-0.03		-0.07
		[-4.32]	[-2.05]		[-1.23]		[-2.79]
β_{SMB}		-0.13	-0.12		-0.03		-0.15
		[-4.22]	[-4.99]		[-0.94]		[-4.33]
β_{HML}		-0.12	-0.01		-0.14		0.06
		[-3.65]	[-0.23]		[-3.61]		[1.52]
$\beta_{\text{UMD}^{\text{net}}}$			0.18		0.18		0.18
			[9.77]		[5.93]		[7.24]
$\beta_{\text{CAR3}^{\text{net}}}$			0.29		0.29		0.29
			[5.54]		[3.72]		[4.19]
adj.-R^2 (%)		9.1	41.0		34.1		49.5

Table 7 continued

	Full sample			1/75–12/93		1/94–12/12	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel C: y = CAR3$^{\text{net}}$							
α	0.19	0.29	0.10	0.28	0.12	0.11	0.06
	[2.50]	[3.74]	[1.46]	[3.25]	[1.38]	[0.84]	[0.58]
β_{MKT}		-0.08	-0.03		0.00		-0.05
		[-4.28]	[-2.12]		[0.07]		[-1.96]
β_{SMB}		-0.03	-0.00		-0.03		-0.00
		[-1.20]	[-0.21]		[-1.12]		[-0.06]
β_{HML}		-0.11	-0.03		0.04		-0.08
		[-4.13]	[-1.27]		[1.33]		[-2.26]
$\beta_{\text{UMD}^{\text{net}}}$			0.13		0.12		0.12
			[7.79]		[4.74]		[5.24]
$\beta_{\text{SUE}^{\text{net}}}$			0.22		0.20		0.25
			[5.54]		[3.72]		[4.19]
adj.-R^2 (%)		5.7	34.6		23.7		40.2

Panel C shows that CAR3, which is more expensive to trade than SUE, and suffered greater performance deterioration over time, generated statistically significant net returns over the whole sample, but completely insignificant net returns over the second half of the sample. Its abnormal returns relative to the Fama and French factors and the other two momentum strategies were also insignificant over the whole sample, suggesting that in practice CAR3 does not significantly improve the opportunity set for investors already trading SUE.

5.1. A portfolio perspective

Another way to quantify the potential value of momentum strategies to real investors is to consider the potential Sharpe ratios that could have been achieved using the strategies. Table 8 reports the portfolio weights in ex post mean-variance efficient portfolios of various combinations of the momentum strategies and the three Fama and French factors. Panel A provides full sample results. The first four specifications show that all three of the momentum strategies have reasonably high Sharpe ratios over the sample, though this is

Table 8

Ex-post mean-variance efficient portfolios

This table gives weights in the ex-post mean-variance efficient portfolio for various combinations of the net of transaction cost momentum factors (UMD^{net}, SUE^{net}, and $CAR3^{net}$) and the Fama and French factors (MKT, SMB, and HML), as well as the realized annual Sharpe ratios (S.R.) of these portfolios. The full sample covers January 1975 through December 2012, with the dates determined by the data requirements for making the SUE and CAR3 strategies. The early and late samples are January 1975 through December 1993 and January 1994 through December 2012, respectively.

	Strategy weight in ex-post MVE portfolio and portfolio Sharpe ratio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full sample results									
UMD^{net}	1.00			-0.03		0.19			0.00
SUE^{net}		1.00		0.70			0.42		0.31
$CAR3^{net}$			1.00	0.33				0.42	0.16
MKT					0.28	0.23	0.16	0.17	0.15
SMB					0.24	0.16	0.16	0.13	0.14
HML					0.48	0.42	0.26	0.28	0.24
S.R.	0.33	0.55	0.41	0.57	0.81	0.98	1.16	1.02	1.19
Panel B: Early sample (1/75–12/93) results									
UMD^{net}	1.00			0.01		0.24			0.02
SUE^{net}		1.00		0.52			0.47		0.34
$CAR3^{net}$			1.00	0.46				0.48	0.17
MKT					0.27	0.17	0.12	0.13	0.10
SMB					0.19	0.15	0.11	0.12	0.10
HML					0.54	0.44	0.31	0.27	0.27
S.R.	0.59	0.87	0.75	0.97	1.09	1.34	1.64	1.39	1.69
Panel C: Late sample (1/94–12/12) results									
UMD^{net}	1.00			-0.03		0.17			-0.00
SUE^{net}		1.00		0.95			0.42		0.33
$CAR3^{net}$			1.00	0.08				0.39	0.12
MKT					0.32	0.29	0.21	0.21	0.20
SMB					0.24	0.15	0.16	0.13	0.14
HML					0.45	0.39	0.21	0.28	0.21
S.R.	0.18	0.34	0.19	0.34	0.58	0.69	0.84	0.71	0.85

clearly highest for SUE^{net}, which is the only momentum strategy that realizes a higher net Sharpe ratio over the sample than the 0.48 delivered by the market. They also show that access to all three momentum strategies hardly improves the Sharpe ratio over that available from SUE^{net} alone (0.57 vs. 0.55). The last five specifications show that adding any of the momentum strategies to the opportunity set of an investor already trading the three Fama and French factors yields significant Sharpe ration improvements (from 0.81 to from 0.98 to 0.16), but that including price momentum and the strategy based on CAR3 again yield only marginal improvements above those realized from adding SUE alone (1.19 vs 1.16). Panel B and C show consistent subsample results, and suggest that if anything these conclusions have strengthened over time.

6 Past performance and future comovements

While the previous sections demonstrate that past performance is not strongly associated with cross sectional variation in average returns, at least after controlling for earnings surprises, past performance is important for understanding the cross section of realized returns. This is partly mechanical, as sorting on past performance is sorting, in part, on covariances. Given two stocks that covary strongly, when one performs well the other is also more likely to do so, so stocks that covary strongly are more likely to end up in the winners' portfolio together. Similarly, stocks that have negative market-residual covariance are more likely to end up in opposite sides of a momentum strategy, because when one outperforms the market the other is more likely to underperform, and vice-versa. The relatively high average covariance of stocks in the winners' (or losers') portfolio, and the relatively low average covariance between stocks in the winners' and losers' portfolios, helps explain realized return variation.

Figure 7 provides graphical evidence of these effects. Panel A shows the volatilities of value-weighted portfolios obtained by decile sorting, using NYSE breaks, on the three momentum characteristics, past performance ($r_{2,12}$), standardized unexpected earnings

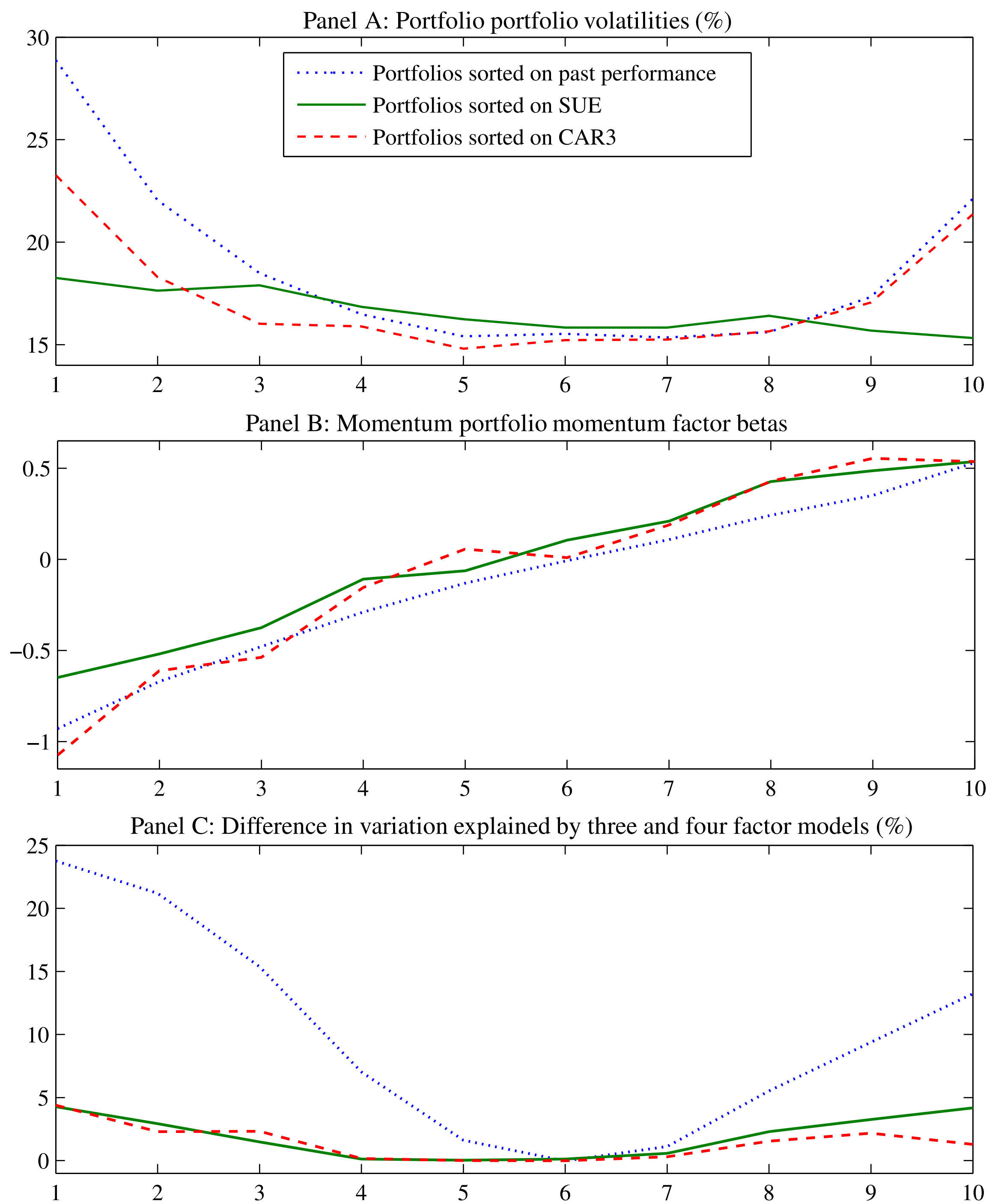

Fig. 7. Momentum portfolio return properties. Panel A shows the volatilities of value-weighted portfolios, decile sorted using NYSE breaks, on past performance $r_{2,12}$, SUE, and CAR3. Panel B shows the portfolios' loadings on the momentum factor constructed on the basis of the same momentum characteristic (UMD, SUE, or CAR3), from time-series regressions that include the three Fama and French factors. Panel C shows the additional return variation explained by the momentum factor for each portfolio. It gives the difference in the adjusted R^2s from three- and four-factor time-series regressions.

(SUE), and three day cumulative abnormal returns (CAR3). The portfolios sorted on the return based variables, $r_{2,12}$ and CAR3, exhibit volatilities that are U-shaped in the portfolio number. This is unsurprising, as more volatile stocks are more likely to exhibit large returns, positive or negative, and thus end up in the tail portfolios. In contrast, the portfolios sorted on SUE exhibit a downward sloping volatility profile. Stocks that have experienced growth in earnings per share appear, on average, less volatile.

Panel B reports momentum loadings for each portfolio from four-factor time-series regressions. These regressions include, as explanatory returns, the returns to the three Fama and French factors, and the returns to the momentum factor based on the same sorting characteristic used to construct test portfolio. The figure shows that the three different momentum characteristics yield similar variation in the corresponding momentum factor loadings across the portfolios.

Panel C shows that despite the similar dispersion in momentum factor loadings, UMD is far more important for explaining realized return variation in portfolios sorted on past performance than the SUE or CAR3 factors are for explaining realized return variation in portfolios sorted on earnings surprises. All three factors contribute more to explaining the performance of the tail portfolios, which have larger momentum tilts, positive or negative, than the portfolios in the middle. The figure shows, however, that even for these tail portfolios the earnings momentum factors only contribute modestly to explaining realized performance, increasing the return variation explained by the model in all cases by less than 5%. This is primarily because the three-factor model performs relatively well explaining these portfolios' realized performance, explaining in excess of 85% of the returns variation for even the extreme positive and negative surprise portfolios. UMD, in contrast, is extremely important for explaining the variation in the extreme price momentum portfolios. These portfolios experience much more return variation driven by comovement among stocks with similar past performance. Including UMD as an explanatory factor consequently increases the return variation explained by the model by almost 15% for the extreme winner portfolio, and almost 25% for the extreme loser portfolio.

7. Conclusion

Past performance predicts cross sectional variation in average stock returns because strong past performance is a signal of positive moves in fundamentals. After controlling for fundamentals, past performance does not provide significant additional information regarding expected returns. Fundamentally, momentum is fundamental momentum.

Past performance should not be ignored, however, when trading momentum. Earnings momentum strategies constructed without regard for past price performance take unintended, performance impairing, positions in price momentum. Designing earnings momentum strategies explicitly to avoid price momentum reduces the strategies' volatilities, and eliminates their tendency to occasionally crash, without significantly reducing expected returns. This results in higher Sharpe ratios and smaller drawdowns.

Recent past performance may also provide an informative signal in other markets. A similar phenomenon is observed with De Bondt and Thaler's (1985) long run reversals. Value and size explain the performance of stock market strategies based on long run reversal, because stocks that have experienced long periods of underperformance tend to have low valuations. Because of this correlation, poor long run past performance may also signal value in markets in which direct measures of value are unavailable, e.g., markets for assets that have no accounting variables that could be used to scale prices. Similarly, in markets where fundamentals are not directly observable, or are difficult to quantify, recent past performance helps signal fundamental innovations, or at least the markets' interpretation of these innovations.

Past performance is also important for understanding the cross section of realized returns. Recent winners tend to perform strongly together, and poorly precisely when recent losers perform strongly. These strong comovements introduce significant risk to strategies that tilt toward price momentum, contributing volatility even when the strategies are well diversified in names, and negative skew that exposes the strategies to large drawdowns. Accounting for these tilts, when they are present, dramatically improves the explanatory power that asset pricing models have explaining variation in realized returns.

Appendix Table A1

SUE and CAR3 strategies' underlying portfolios

This table reports the average monthly excess returns of the portfolios underlying the earnings momentum factors SUE and CAR3, and results of time-series regressions of the excess returns to these portfolios onto the three Fama and French factors, MKT, SMB, and HML, and the price momentum factor, UMD. The portfolios are constructed using either large or small capitalization stocks, defined as those with above and below median NYSE market capitalization, and hold stocks ranked in the highest or lowest 30% by the earnings surprise measure, also using NYSE breaks. Returns are value-weighted, and the sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Portfolios sorted SUE			Portfolios sorted on CAR3		
	Low	High	H−L	Low	High	H−L
Panel A: Large cap strategies						
$E[r^e]$	0.49	0.76	0.27	0.50	0.76	0.26
	[2.13]	[3.73]	[2.77]	[2.11]	[3.37]	[2.95]
α	-0.11	0.13	0.24	-0.08	0.13	0.21
	[-1.98]	[2.80]	[2.69]	[-1.49]	[2.54]	[2.39]
β_{MKT}	1.06	0.97	-0.09	1.06	1.02	-0.04
	[83.0]	[90.5]	[-4.36]	[89.8]	[88.0]	[-2.21]
β_{SMB}	-0.10	-0.19	-0.09	-0.03	-0.02	0.02
	[-5.27]	[-12.4]	[-3.20]	[-2.02]	[-1.12]	[0.56]
β_{HML}	0.03	0.03	-0.00	-0.04	-0.07	-0.04
	[1.81]	[1.99]	[-0.09]	[-2.08]	[-4.15]	[-1.19]
β_{UMD}	-0.08	0.10	0.18	-0.11	0.03	0.14
	[-6.12]	[9.96]	[9.01]	[-9.46]	[2.96]	[7.44]
Panel B: Small cap strategies						
$E[r^e]$	0.61	1.52	0.91	0.52	1.32	0.80
	[2.08]	[5.54]	[9.69]	[1.64]	[4.37]	[12.7]
α	-0.25	0.55	0.79	-0.36	0.38	0.74
	[-4.51]	[9.05]	[10.3]	[-6.74]	[7.83]	[13.0]
β_{MKT}	1.04	1.05	0.01	1.12	1.10	-0.02
	[82.3]	[76.3]	[0.69]	[91.5]	[98.0]	[-1.41]
β_{SMB}	0.93	0.78	-0.15	1.01	0.93	-0.08
	[51.5]	[39.6]	[-5.99]	[57.6]	[57.7]	[-4.35]
β_{HML}	0.29	0.24	-0.04	0.09	0.10	0.01
	[15.0]	[11.7]	[-1.58]	[4.98]	[5.80]	[0.33]
β_{UMD}	-0.27	-0.01	0.26	-0.23	-0.10	0.13
	[-21.9]	[-0.47]	[15.3]	[-19.9]	[-9.30]	[10.6]

Appendix Table A2

Conditional price and earnings momentum strategy performance, alternate construction

This table presents results of time-series regressions of the form:

$$y_t = \alpha + \boldsymbol{\beta}'\mathbf{X}_t + \varepsilon_t$$

where the y_t are the monthly excess returns to either UMD (specifications one and two), the earnings momentum factor SUE (specifications three and four), the price momentum factor constructed to be neutral with respect to earnings momentum UMD|SUE (specifications five and six), and the earnings momentum factor constructed to be neutral with respect to price momentum SUE|$r_{2,12}$ (specifications seven and eight). Explanatory factors are taken from the same set of strategies. The conditional factors are constructed similar to UMD, but sort stocks on the primary sorting characteristic ($r_{2,12}$ or SUE) from among stocks matched on the other characteristic. The initial match selects triples of stocks matched on the conditioning variable, which yields similar name diversification to that obtained from a univariate tertile sort. Explanatory factors are taken from the same set of strategies. The sample covers January 1975 through December 2012.

	dependent variable											
	y = UMD			y = SUE			y = UMD|SUE			y = SUE|$r_{2,12}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
α	0.64	0.29	0.04	0.59	0.15	0.01	0.25	-0.15	-0.03	0.43	0.20	0.17
	[3.03]	[4.09]	[0.57]	[7.14]	[2.14]	[0.12]	[1.77]	[-3.26]	[-0.58]	[8.42]	[4.75]	[5.08]
$\beta_{\text{UMD}\vert\text{SUE}}$		1.40	1.43			0.31						
		[61.0]	[67.1]			[20.2]						
$\beta_{\text{SUE}\vert r_{2,12}}$			0.56		1.03	1.18						
			[9.30]		[17.6]	[27.3]						
β_{UMD}								0.64	0.70			-0.14
								[61.0]	[60.8]			[-16.1]
β_{SUE}									-0.29		0.39	0.59
									[-9.74]		[17.6]	[27.4]
adj.-R^2 (%)		89.1	90.8		40.5	68.7		89.1	91.0		40.5	62.1

Appendix Table A3

Conditional strategies' underlying portfolios

This table reports the average monthly excess returns of the portfolios underlying the conditional momentum factors UMD|SUE and SUE|$r_{2,12}$, and results of time-series regressions of the excess returns to these portfolios onto the three Fama and French factors, MKT, SMB, and HML, and the price momentum factor, UMD. The portfolios are constructed using either large or small capitalization stocks, defined as those with above and below median NYSE market capitalization, and hold stocks ranked highest or lowest by the primary sorting characteristic ($r_{2,12}$ or SUE) from among groups of seven stocks most closely matched on the other characteristic. Returns are value-weighted, and the sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Conditional momentum: SUE matched, then sorted on $r_{2,12}$			Conditional PEAD: $r_{2,12}$ matched, then sorted on SUE		
	Low	High	H−L	Low	High	H−L
Panel A: Large cap strategies						
$E[r^e]$	0.55	0.93	0.38	0.54	0.77	0.23
	[2.08]	[3.62]	[1.58]	[2.44]	[3.82]	[2.28]
α	0.25	-0.10	-0.36	-0.14	0.19	0.33
	[3.37]	[-1.23]	[-3.01]	[-2.01]	[2.99]	[3.15]
β_{MKT}	1.02	1.09	0.07	1.04	0.94	-0.10
	[59.0]	[56.3]	[2.46]	[67.2]	[64.3]	[-4.10]
β_{SMB}	-0.11	0.09	0.20	-0.14	-0.19	-0.05
	[-4.47]	[3.06]	[5.00]	[-6.29]	[-8.93]	[-1.42]
β_{HML}	-0.01	-0.04	-0.03	0.05	0.00	-0.04
	[-0.56]	[-1.51]	[-0.72]	[2.00]	[0.21]	[-1.17]
β_{UMD}	-0.57	0.44	1.01	-0.01	-0.01	-0.00
	[-34.0]	[23.7]	[38.3]	[-0.41]	[-0.68]	[-0.15]
Panel B: Small cap strategies						
$E[r^e]$	0.69	1.22	0.52	0.68	1.57	0.89
	[1.88]	[3.97]	[2.08]	[2.44]	[5.71]	[11.4]
α	0.07	-0.06	-0.12	-0.31	0.59	0.89
	[0.67]	[-0.83]	[-1.08]	[-5.43]	[8.86]	[11.1]
β_{MKT}	1.15	1.08	-0.07	1.02	1.06	0.03
	[49.9]	[67.7]	[-2.75]	[79.4]	[69.2]	[1.80]
β_{SMB}	1.00	1.04	0.04	0.92	0.80	-0.12
	[30.2]	[45.4]	[0.96]	[49.6]	[36.4]	[-4.55]
β_{HML}	0.12	0.10	-0.02	0.29	0.26	-0.02
	[3.48]	[4.32]	[-0.43]	[14.6]	[11.3]	[-0.86]
β_{UMD}	-0.78	0.31	1.09	-0.14	-0.11	0.03
	[-35.1]	[20.0]	[42.5]	[-10.9]	[-7.14]	[1.71]

Appendix Table A4

Conditional strategies' underlying portfolios, alternative construction

This table reports the average monthly excess returns of the portfolios underlying the conditional momentum factors UMD|SUE and SUE|$r_{2,12}$, and results of time-series regressions of the excess returns to these portfolios onto the three Fama and French factors, MKT, SMB, and HML, and the price momentum factor, UMD. The portfolios are constructed using either large or small capitalization stocks, defined as those with above and below median NYSE market capitalization, and hold stocks ranked highest or lowest by the primary sorting characteristic ($r_{2,12}$ or SUE) from triples of stocks most closely matched on the other characteristic. Returns are value-weighted, and the sample covers January 1975 through December 2012, dates determined by the data requirements for making the SUE and CAR3 strategies.

	Conditional momentum: SUE matched, then sorted on $r_{2,12}$			Conditional PEAD: $r_{2,12}$ matched, then sorted on SUE		
	Low	High	H−L	Low	High	H−L
Panel A: Large cap strategies						
$E[r^e]$	0.56	0.77	0.21	0.54	0.77	0.24
	[2.57]	[3.50]	[1.40]	[2.52]	[3.89]	[3.27]
α	0.14	-0.09	-0.23	-0.13	0.18	0.32
	[2.65]	[-2.13]	[-2.76]	[-3.33]	[4.08]	[4.31]
β_{MKT}	0.97	1.03	0.06	1.02	0.95	-0.07
	[81.3]	[102.1]	[3.27]	[111.9]	[92.1]	[-4.24]
β_{SMB}	-0.17	-0.04	0.13	-0.12	-0.18	-0.06
	[-9.96]	[-2.71]	[4.74]	[-8.74]	[-12.0]	[-2.62]
β_{HML}	0.05	-0.00	-0.05	0.03	0.00	-0.02
	[2.85]	[-0.02]	[-1.77]	[1.98]	[0.22]	[-0.94]
β_{UMD}	-0.31	0.28	0.59	0.00	-0.01	-0.01
	[-27.1]	[28.8]	[31.9]	[0.21]	[-0.61]	[-0.49]
Panel B: Small cap strategies						
$E[r^e]$	0.90	1.20	0.30	0.80	1.38	0.58
	[2.88]	[4.31]	[1.97]	[2.89]	[5.07]	[10.6]
α	0.12	0.04	-0.08	-0.20	0.40	0.60
	[2.09]	[0.78]	[-1.21]	[-4.42]	[7.72]	[10.7]
β_{MKT}	1.10	1.05	-0.05	1.03	1.05	0.01
	[83.8]	[95.6]	[-3.24]	[99.4]	[87.3]	[1.08]
β_{SMB}	0.89	0.92	0.04	0.90	0.81	-0.09
	[46.9]	[58.4]	[1.60]	[59.9]	[46.9]	[-4.73]
β_{HML}	0.26	0.22	-0.04	0.29	0.28	-0.01
	[13.1]	[13.5]	[-1.53]	[18.2]	[15.2]	[-0.54]
β_{UMD}	-0.51	0.15	0.66	-0.12	-0.12	-0.01
	[-39.9]	[14.6]	[43.8]	[-11.4]	[-10.5]	[-0.55]

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