Is momentum really momentum?[*]

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Abstract

Momentum is primarily driven by firms' performance 12 to seven months prior to portfolio formation, not by a tendency of rising and falling stocks to keep rising and falling. Strategies based on recent past performance generate positive returns but are less profitable than those based on intermediate horizon past performance, especially among the largest, most liquid stocks. These facts are not particular to the momentum observed in the cross section of US equities. Similar results hold for momentum strategies trading international equity indices, commodities, and currencies.

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1. Introduction

Momentum, the tendency of an object in motion to stay in motion, does not accurately describe the returns to buying winners and selling losers. The stocks that have risen the most over the past six months, but performed poorly over the first half of the preceding year, significantly under-perform those stocks that have fallen the most over the past six months but performed strongly over the first half of the preceding year. That is, intermediate horizon past performance, measured over the period from 12 to seven months prior, seems to better predict average returns than does recent past performance. This fact is difficult to reconcile with the traditional view of momentum, that rising stocks tend to keep rising, while falling stocks tend to keep falling, i.e., a short run autocorrelation in prices.

The fact that intermediate horizon past performance has more power than recent past performance predicting returns can be seen in a variety of ways. In Fama-MacBeth regressions of stocks' returns on their past performance, the coefficient on intermediate past performance is significantly higher than that on recent past performance. Momentum trading strategies based on intermediate past performance generate larger, more significant returns than those based on recent past performance and have significant alphas relative to the Fama-French four factor model, while the strategies based on recent past performance do not. Portfolios double sorted on recent and intermediate horizon past performance exhibit roughly twice the variation in returns across the intermediate past performance dimension as they do in the recent past performance dimension.

Moreover, while the predictive power of recent returns seems to have diminished over time, that of intermediate past returns has not. Strategies based on recent past performance were exceptionally profitable in the 1950s and 1960s, but have not performed as well since. Strategies based on intermediate horizon past performance have performed consistently over time and, if anything, have been more profitable over the last 40 years. This divergence in performance also has been accompanied by an increased correlation on the strategies' returns. Because recent return strategies covary significantly with an intermediate past return factor, even when they are explicitly constructed to be intermediate past return neutral, over the last several decades the recent return strategies contribute little to the opportunity set of an investor already trading the three Fama-French factors and intermediate horizon momentum.

These results are not particular to the momentum observed in the cross section of US equities. Similar results hold for momentum strategies constructed in other asset classes. Momentum strategies that trade industries, investment styles, international equity indices, commodities, and currencies all exhibit the same phenomena. The Sharpe ratios of the strategies based on intermediate horizon past performance are more than twice as large as the Sharpe ratios of the strategies based on recent past performance. The strategies based on intermediate horizon past performance also all have large, highly significant information ratios relative to the strategies based on recent past performance. The strategies based on recent past performance never generate significant abnormal returns relative to the strategies based on intermediate horizon past performance.

Practically, the recognition that the abnormal returns to buying winners and selling losers derives primarily from intermediate horizon, not recent, past performance aids in the construction of more profitable strategies. This is especially true among the largest, most liquid stocks, which exhibit more momentum than is commonly recognized. The value-weighted strategy, restricted to large stocks (largest quintile by market equity using New York Stock Exchange break points, made up of roughly the three hundred largest firms in the economy), which buys (sells) the top (bottom) quintile of performers over the period 12 to seven months prior to portfolio formation, generated average returns of almost 10% per year from January 1927 through December 2008. The fact that Fortune 500 companies exhibit strong momentum suggests that properly designed momentum strategies are profitable on a greater scale than that estimated by Korajczyk and Sadka (2004) and that the trading cost critique of Lesmonda, Schill, and Zhou (2004) is significantly overstated.

Theoretically, the return predictability implied by the data, which looks more like an echo than momentum, poses a significant difficulty for stories that purport to explain momentum. None of the popular explanations, either behavioral (e.g., Barberis, Shleifer and Vishny, 1998, Hong and Stein, 1999, and Daniel, Hirshleifer and Subrahmanyam, 1999) or rational (e.g., Johnson, 2002, and Sagi and Seasholes, 2007), delivers the observed term structure of momentum information, which exhibits significant information in past performance at horizons of 12 to seven months, recent returns that are largely irrelevant after controlling for performance at intermediate horizons, and the abrupt drop-off at 12 months, beyond which there is no return predictability after controlling for value.

My primary result– that intermediate horizon past performance, not recent past performance, drives momentum– cannot be explained by any known results. It is not explained by the 12 month effect identified by Jegadeesh (1990) and studied in detail by Heston and Sadka (2008). It is robust to controlling for earnings momentum, which explains short horizon momentum but not intermediate horizon momentum. It cannot be explained by capital gains overhang or disposition effects. It is essentially unrelated to the consistency of performance result of Grinblatt and Moskowitz (2004).

The remainder of the paper is organized as follows. Section 2 shows that the profitability of momentum strategies derives primarily from intermediate horizon past performance, not recent past performance. Section 3 shows this formally. In particular, it shows that the coefficient on intermediate past performance significantly exceeds that on recent past performance in Fama-MacBeth regressions of firms' returns; momentum strategies based on intermediate horizon past performance are more profitable than those based on recent past performance, and have significant information ratios relative to the

Fama-French four-factor model while those based on recent past performance do not; and double sorting on both intermediate horizon and recent past performance yields substantially larger returns spreads along the intermediate horizon dimension. Section 4 shows that the disparity in the power of intermediate horizon and recent past performance to predict returns is especially acute among large, liquid stocks. Section 5 shows that these results also hold for momentum strategies that trade other asset classes, including industries, investment styles, international equity indices, commodities, and currencies. Section 6 places my primary result in the context of the literature and demonstrates its robustness. Section 7 concludes.

2. The term-structure of momentum

Previous research has devoted significant attention to the length of the test period over which past performance is evaluated when constructing momentum portfolios. For example, Jegadeesh and Titman (1993) consider the "J/K-strategies," which form portfolios based on stock performance over the previous J months (excluding the last week or month prior to portfolio formation, to remove the large short-horizon reversals associated with bid-ask bounce) and hold the portfolios for K months, where $J, K \in \{3, 6, 9, 12\}$.

Almost no attention has been devoted, however, to how long before portfolio formation this test period should end. This gap reflects, perhaps, the presumption that the returns to buying winners and selling losers was due to momentum, short-run autocorrelation in stock returns, and that the power of past returns to predict future returns therefore decays monotonically over time. In this section I show that this assumption is false, by considering the returns to momentum strategies while varying the length of the test period and the time between the test period and portfolio formation. I fix the holding period at one month to keep the number of strategies under consideration manageable.

2.1. Data and portfolio construction

The data cover the sample period from January 1926 through December 2008 and include all stocks in the Center for Research in Securities Prices (CRSP) universe. The Fama-French up-minus-down factor (UMD) replicated in this data generates a monthly return series more than 99% correlated with the series posted on Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

Momentum strategies are constructed each month by buying winners and selling losers, where these are defined as the upper and lower decile, by NYSE breaks, of cumulative returns over a test period. The n-m strategy is based on portfolios sorted on $r_{n,m}$, denoting cumulative returns from n to m months (inclusive) prior to portfolio formation. The n-m strategy and its return series are both denoted $\mathrm{MOM}_{n,m}$. I consider value-weighted and equal-weighted strategy returns. I construct strategies using all available data, employing returns beginning in January 1926.

2.2. Strategies based on past performance in a single month

Fig. 1 shows the performance of strategies formed on the basis of performance in a single month, i.e., of winner-minus-loser portfolios where winners and losers are defined as the top and bottom decile of performance, respectively, in the month lag prior to portfolio formation. Strategies are formed using a single month's returns realized from one month to 15 months prior to portfolio formation. The figure depicts these strategies' average monthly returns, monthly standard deviations, and realized annual Sharpe ratios. Value-weighted results appear as black bars, and equal-weighted results are depicted as grey bars.

Panel A shows strategies' monthly average returns. The general trend is upward sloping spreads, i.e., spreads that increase with time between performance evaluation and portfolio formation, which fall off a cliff after 12 months. This profile is largely consistent with

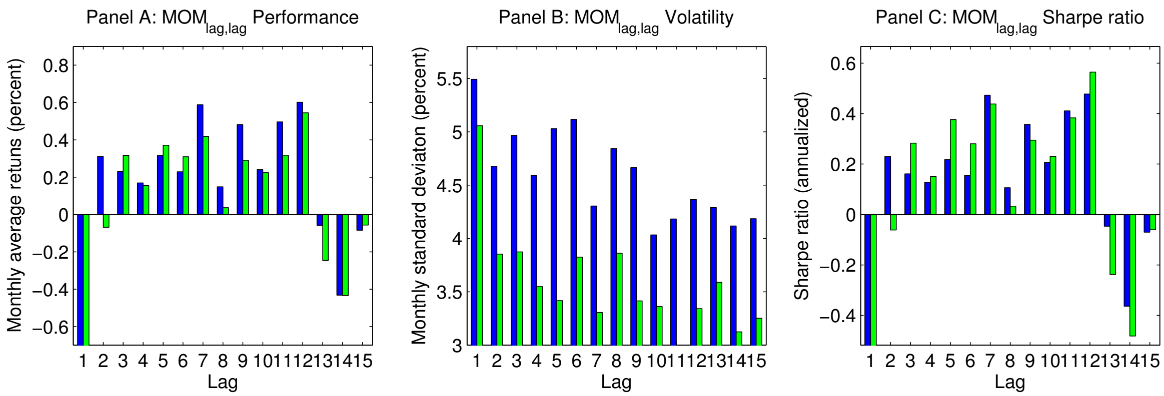

Fig.1. Marginal strategy performance. This figures shows the average monthly returns (Panel A), monthly standard deviations (Panel B) and annual Sharpe ratio (Panel C) to winners-minus-losers strategies. Winners and losers are defined as the top and bottom deciles of performance in a single month, respectively, starting lag months prior to portfolio formation. Dark bars show value-weighted results and light bars show equal-weighted results. Average monthly returns for the one month reversals are -0.98% (value-weighted) and -2.92% (equal-weighted). The sample covers April 1927 to December 2008.

the Heston and Sadka (2008) estimate, from Fama-MacBeth regressions, of the slope coefficient of past performance on expected returns as a function of historical lag. The upward sloping term-structure is inconsistent with the common conception of momentum as a short-run autocorrelation in returns. The abrupt drop-off after one year is one of the most striking features of the figure and poses a significant hurdle for stories, either rational or behavioral, that attempt to explain momentum.

Panel B depicts the standard deviation of the strategies' monthly returns. It shows a generally downward sloping relation between the time between performance evaluation and portfolio formation and a strategy's volatility. The observed pattern is consistent with mean-reverting stochastic volatility. The portfolio selection criteria, which select for stocks that have experienced large movements, bias both the winner and loser portfolios toward stocks that have high volatility and, consequently, toward stocks that have volatilities higher than their own long-run average. A longer interval prior to portfolio formation provides time for these volatilities to revert downward.

Panel C shows the strategies' Sharpe ratios. The pattern here is largely inherited from the return spreads, tilted counterclockwise by the downward sloping volatility profile. That is, the term-structure of performance slopes up even more steeply than the term-structure of expected returns. The figure consequently suggests that the months closest to portfolio formation contribute little to the performance of the typical momentum strategy.

2.3. Portfolios sorted on recent and intermediate past performance

Fig. 1 suggests that past performance at intermediate horizons contributes more to the profitability of momentum strategies than does past performance at recent horizons. The simplest way to test this hypothesis is to compare the profitability of strategies formed on the basis of recent and intermediate horizon past performance. Recent and intermediate horizons are defined here simply as the near and distant halves of the performance evaluation period most commonly employed in the construction of momentum strategies, i.e., using the past performance metrics $r_{6,2}$ and $r_{12,7}$, respectively.

Fig. 2 depicts results of forming portfolios on the basis of intermediate horizon or recent past performance. Each line in the figure shows the average monthly returns to a continuum of quintile-like portfolios, constructed by sorting on $r_{12,7}$ and $r_{6,2}$ (solid and dashed lines, respectively). Each point in the past performance distribution corresponds to a portfolio that holds stocks in Gaussian proportions, where the Gaussian is centered at the point, and has a bandwidth (standard deviation) of 10%. Each portfolio's holdings are therefore concentrated in a 20% range of the past performance distribution and, consequently, behave much like a quintile portfolio. Panel A shows value-weighted results, where the weights correspond to the fraction of firms' market capitalizations held in the portfolio. Panel B shows equal-weighted results, where the weights correspond to dollar values held in the portfolio. Returns are shown either in excess of the average market return (value-weighted results) or in excess of the average stock's average return (equal-weighted

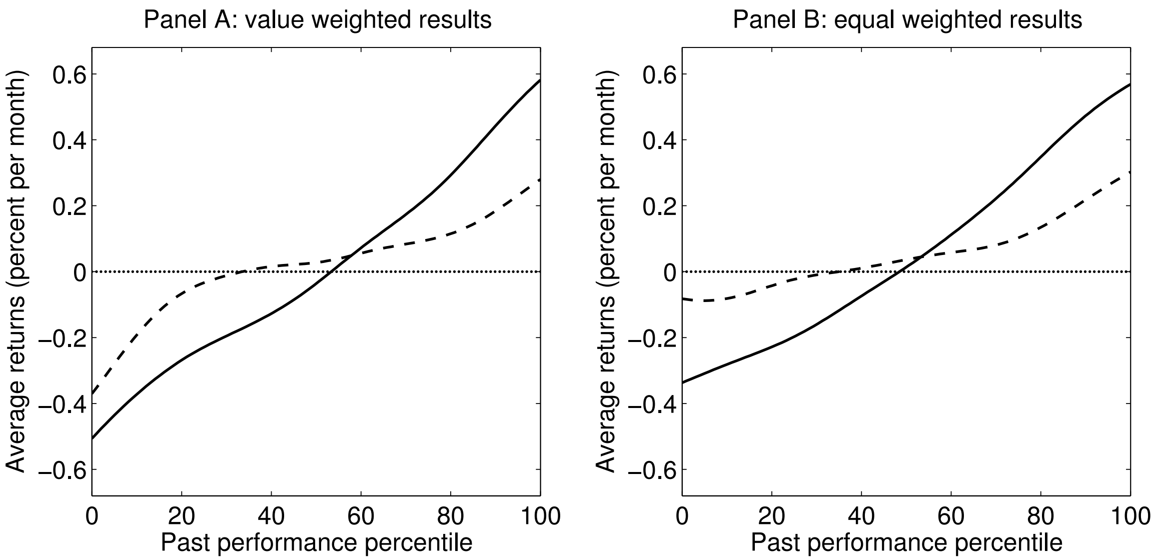

Figure 2. Average returns to portfolios sorted on $r_{12,7}$ and $r_{6,2}$. This figure shows average monthly returns to portfolios sorted on intermediate horizon past performance (solid line) and recent past performance (dashed line), in excess of the average stock's returns. For each point in the past performance distribution, stocks are held in Gaussian proportions, centered at the point in question, with a standard deviation of 10%. Portfolios are constructed each month. Panel A shows value-weighted results, where the weights represent the fractions of firms' market capitalizations held in the portfolio. Panel B shows equal-weighted results, where the weights correspond to dollar values held in the portfolio. The sample period covers January 1927 through December 2008.

results). Portfolios are constructed each month, and the sample period covers January 1927 through December 2008.

The figure shows a substantially stronger relation between intermediate past performance and expected returns than between recent past performance and expected returns. The relation between intermediate horizon past performance and average returns is strong, and roughly linear, while the relation between recent past performance and average returns is both weaker and concentrated in the tails of the distribution.

The figure seems to contradict the Hong, Lim, and Stein (2000) contention that the bulk of momentum profits come from the short side. Hong, Lim, and Stein argue that a momentum strategy's profitability is driven by losers' under-performance, and not by winners' out-performance. The figure suggests that both sides contribute roughly equally to a momentum strategy's profitability.

3. Information in intermediate horizon past performance

Fig. 2 suggests that momentum derives primarily from past performance at intermediate horizons, not recent past performance. This section investigates this hypothesis formally.

3.1. Parametric results

Table 1 reports results of Fama-MacBeth regressions of returns on recent and intermediate horizon past performances, $r_{6,2}$ and $r_{12,7}$, and controls for past month's performance, size, and book-to-market.[1]

The first column shows results over the entire 82-year sample, spanning January 1927 to December 2008. The coefficient in intermediate horizon past performance is nearly twice that on recent past performance, and the difference is statistically significant. The difference is not driven by the fact that the intermediate horizon evaluation period covers six months while the recent past performance covers only five. Defining intermediate horizon past performance as performance over the first five months of the preceding year yields qualitatively identical results.

The second two columns show results in the early and late halves of the sample, respectively, January 1927 to December 1967 and January 1968 to December 2008. The

[1] The size control is the log of firms' market capitalizations, lagged one month. The book-to-market control is the log of book-to-market, where book-to-market is book equity (shareholder equity, plus deferred taxes, minus preferred stock) scaled by market equity lagged six months, and is updated at the end of each June using accounting data from the fiscal year ending in the previous calendar year. For the components of shareholder equity, I employ tiered definitions largely consistent with those used by Fama and French (1993) to construct their high-minus-low factor, HML. Stockholders equity is as given in Compustat (SEQ) if available, or else common equity plus the carrying value of preferred stock (CEQ + PSTX) if available, or else total assets minus total liabilities (AT - LT). Deferred taxes is deferred taxes and investment tax credits (TXDITC) if available, or else deferred taxes and/or investment tax credit (TXDB and/or ITCB). Prefered stock is redemption value (PSTKR) if available, or else liquidating value (PSTKRL) if available, or else carrying value (PSTK). Prior to the availability of Compustat, I employ the Davis, Fama and French (2000) book equity data. Independent variables are winsorized at the 1% and 99% levels.

Table 1.
Fama-MacBeth regressions results.

This table reports results from Fama-MacBeth regressions of firms' returns on past performance, measured at horizons 12 to seven months ($r_{12,7}$) and six to two months ($r_{6,2}$). Regressions include controls for prior month's performance ($r_{1,0}$), size (log(ME)), and book-to-market (log(BM)). Independent variables are winsorized each month at the 1% and 99% levels. The sample covers January 1927 to December 2008. The early and late half samples cover January 1927 to December 1967 and January 1968 to December 2008, respectively. The quarter samples cover January 1927 to June 1947, July 1947 to December 1967, January 1968 to June 1988, and July 1988 to December 2008.

	Slope coefficient ($\times 10^2$) and [test-statistic] from regressions of the form $r_{tj} = \boldsymbol{\beta}'\mathbf{x}_{tj} + \epsilon_{tj}$						
	Full sample	Half samples		Quarter samples			
Independent variable	Whole	Early	Late	First	Second	Third	Fourth
$r_{12,7}$	1.15	1.20	1.10	1.22	1.18	1.16	1.03
	[6.15]	[3.58]	[6.68]	[1.98]	[4.50]	[4.76]	[4.68]
$r_{6,2}$	0.61	0.60	0.62	-1.11	2.32	0.46	0.77
	[2.37]	[1.34]	[2.46]	[-1.36]	[6.17]	[1.26]	[2.25]
$r_{1,0}$	-7.79	-9.50	-6.07	-12.0	-6.99	-8.29	-3.85
	[-20.6]	[-15.8]	[-13.6]	[-12.0]	[-11.1]	[-13.7]	[-6.15]
log(ME)	-0.13	-0.16	-0.10	-0.25	-0.07	-0.08	-0.12
	[-3.88]	[-3.08]	[-2.36]	[-2.66]	[-1.65]	[-1.36]	[-1.99]
log(BM)	0.27	0.21	0.33	0.26	0.17	0.48	0.19
	[5.65]	[2.74]	[5.82]	[1.91]	[2.16]	[5.32]	[2.69]
$r_{12,7} - r_{6,2}$	0.54	0.59	0.48	2.33	-1.14	0.70	0.27
	[2.30]	[1.42]	[2.27]	[3.14]	[-3.20]	[2.39]	[0.86]

coefficient estimates on both intermediate horizon and recent past performance are very similar in these subsamples to their whole sample counterparts, though they are estimated more precisely in the late sample, over which the data are more reliable, more stocks were traded, and the market was less volatile.

The last four columns show results over four equal 20.5-year subsamples. The coefficient estimates on intermediate horizon past performance are again stable across subsamples, corresponding closely to the whole sample estimate, and always significant.

This contrasts sharply with recent past performance, on which the coefficient estimates vary widely across subsamples. The coefficient on recent past performance is large and negative, though insignificant, in the prewar sample; extremely large and highly significant from mid-1947 to the end of 1967; positive but insignificant from the beginning of 1968 to mid-1988; and significantly positive, though not particularly large, from mid-1988 to the end of 2008.

Fig. 3 presents similar, more nuanced results graphically. The figure depicts results of rolling ten-year Fama-MacBeth regressions employing the same variables used in the regressions presented in Table 1. Panel A shows the coefficient estimates on both intermediate horizon and recent past performance for each ten-year period ending on the corresponding date. Panel B shows the test-statistics of these coefficient estimates.

The figure depicts results consistent with those from Table 1. The coefficient on $r_{12,7}$ is relatively stable over the entire sample, and generally significant. The coefficient on $r_{6,2}$, in contrast to that on $r_{12,7}$, swings wildly over the sample. While the estimate on $r_{6,2}$ is exceptionally large in the 1950s and 1960s, it is negative from the start of the sample (January 1927) through World War II and frequently close to zero since the inclusion of Nasdaq in CRSP.

Taken as a whole, these Fama-MacBeth regressions suggest that intermediate past returns have surprisingly strong predictive power, even stronger than the predictive power of recent returns. Moreover, the predictive power of recent returns seems to have diminished in recent decades, while that of intermediate past returns has not.

3.2. Spanning tests

Nonparametric tests, which analyze the relations between the returns to momentum strategies formed employing only the early and late information used to construct the standard strategy, generally support these conclusions drawn from the Fama-MacBeth

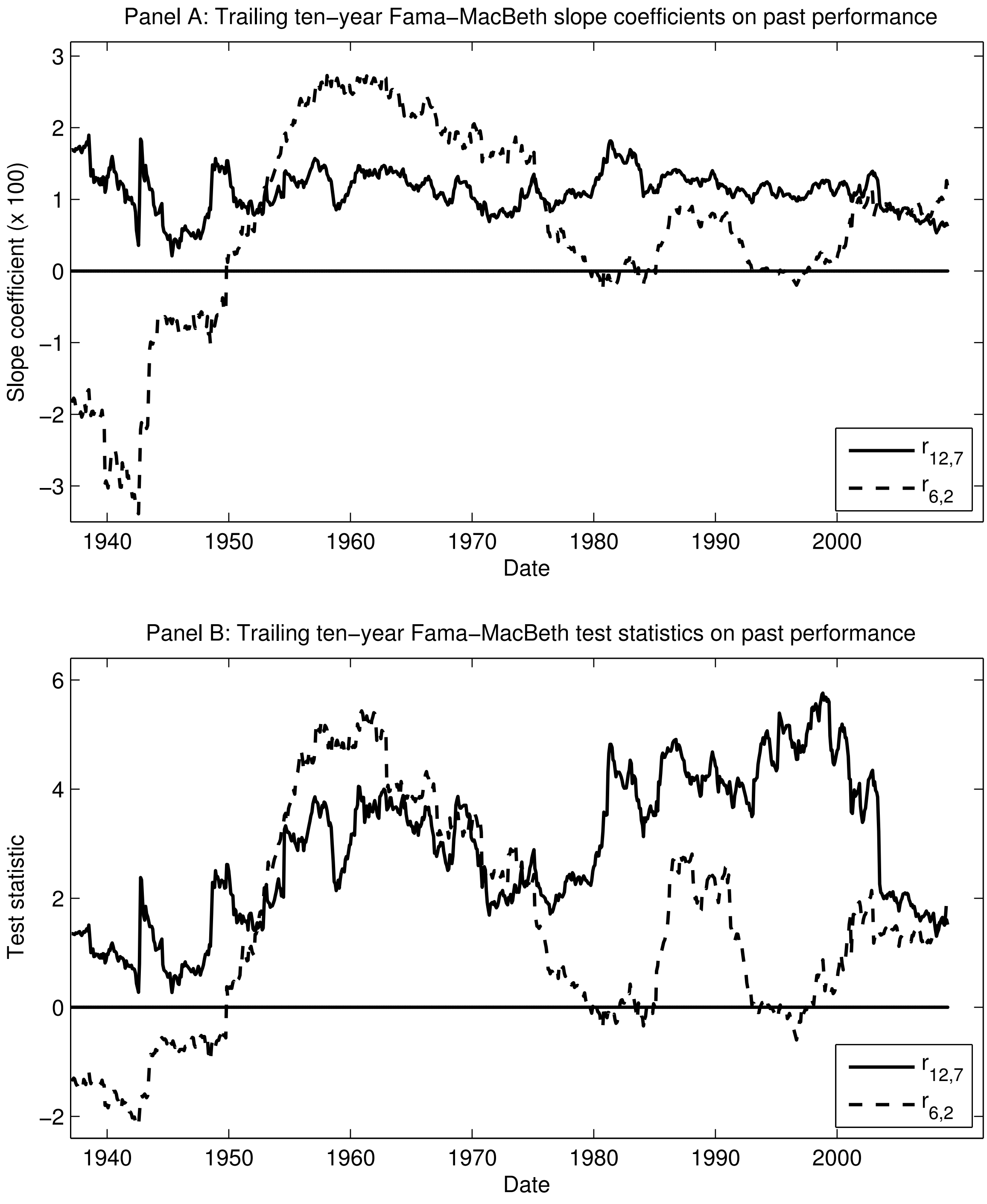

Figure 3. Ten-year trailing slope coefficients on past performance measures. Panel A shows coefficient estimates from rolling ten-year Fama-MacBeth regressions of returns on intermediate horizon past performance ($r_{12,7}$, solid) and recent past performance ($r_{6,2}$, dashed). Regressions include controls for prior month's performance, size, and book-to-market ($r_{1,0}$, ln(ME), and ln(BM), respectively). Panel B shows the test-statistics on these coefficients from the same regressions.

regressions.

These spanning tests regress a test strategy's returns on the returns to one or more explanatory strategies. The intercept's test-statistic is the information ratio of the test strategy benchmarked to the mimicking portfolio constructed from the explanatory strategies. An insignificant intercept suggests the test strategy is inside the span of the explanatory strategies. In this case the test strategy does not add significantly to the investment opportunity set. A high information ratio, i.e., a statistically significant intercept, suggests that adding the test strategy to the investment opportunity set results in an attainable Sharpe ratio that significantly exceeds that which can be achieved with the explanatory strategies alone.

The test strategies I employ in these spanning tests are $\mathrm{MOM}_{12,7}$ and $\mathrm{MOM}_{6,2}$, which each month hold winners and short losers, defined as the upper and lower deciles of $r_{12,7}$ and $r_{6,2}$, respectively, using NYSE breaks. I employ the relatively aggressive decile sort because Fig. 2 suggests the profitability of momentum strategies based on recent past performance derives primarily from the tails of the past performance distribution. Using a less extreme sort (e.g., quintile or tertile) makes the results presented in this paper even stronger. Strategy returns are value-weighted. Tests employing equal-weighting strategy returns yield qualitatively identical results.

Table 2 shows basic properties of the two test strategies, $\mathrm{MOM}_{12,7}$ and $\mathrm{MOM}_{6,2}$, by presenting results of time series regressions of the two strategies' returns on the market, the three Fama-French factors, and the three Fama-French factors plus UMD (up-minus-down). Specifications 1 and 5 show that both strategies generate large, significant average returns. $\mathrm{MOM}_{12,7}$ generates 1.21% per month, while $\mathrm{MOM}_{6,2}$ generates 0.79% per month. While the difference in the two strategies' returns of 0.43% per month is significant at the 10% level, it is not significant at the 5% level (the test-statistic of the difference is 1.78). Specifications 2 and 6 show that both strategies garner significantly negative

Table 2.
Momentum strategy factor loadings.

This table presents results of time-series regressions employing the returns to momentum strategies constructed using intermediate horizon and recent past performance. $\mathrm{MOM}_{n,m}$ is the returns of the winner-minus-loser strategy (deciles, employing NYSE breaks), where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers January 1927 through December 2008.

Independent variable	Intercept (percent per month) and slope coefficient with [test-statistic], under alternative specifications							
	$y = \mathrm{MOM}_{12,7}$				$y = \mathrm{MOM}_{6,2}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	1.21	1.36	1.57	0.43	0.79	1.09	1.27	-0.01
	[5.80]	[6.58]	[8.03]	[3.00]	[3.45]	[5.03]	[6.17]	[-0.10]
MKT		-0.24	-0.14	0.07		-0.51	-0.40	-0.15
		[-6.46]	[-3.80]	[2.64]		[-13.3]	[-9.96]	[-5.60]
SMB			-0.05	0.02			-0.24	-0.16
			[-0.79]	[0.57]			[-3.81]	[-3.84]
HML			-0.62	-0.16			-0.45	0.07
			[-11.3]	[-3.87]			[-7.76]	[1.67]
UMD				1.04				1.17
				[30.9]				[35.7]
Adj. R^2		0.153	0.211	0.657		0.049	0.181	0.562

loadings on the market, similar to those found on conventional 12–2 momentum strategies. Specifications 3 and 7 show that both strategies also have large negative HML loadings in the three-factor model, which results in extremely large three-factor pricing errors, a situation again similar to that found with conventional momentum. Finally, specifications 4 and 8 show that the strategies' alphas relative to the Fama-French four-factor model are much smaller. Including UMD as an explanatory factor reduces the alphas both directly, because the strategies load heavily on UMD, and indirectly, by reducing the magnitudes of the momentum strategies' negative loadings on HML and MKT (market excess return). Nevertheless, the 12–7 strategy generates significant abnormal returns, 0.43% per month with a test statistic of 3.00, relative to the four-factor model. The 6–2 strategies' abnormal four-factor returns are completely insignificant.

Table 3 presents the average returns of these momentum strategies, $\text{MOM}_{12,7}$ and $\text{MOM}_{6,2}$, and results from time series regressions on these strategies' returns on the three Fama-French factors and each other. The first column presents results from the full sample and shows that both strategies have large information ratios relative to the three Fama-French factors and each other. Panel A shows that the 12–7 strategy's abnormal returns relative to the three Fama-French factors and the 6–2 strategy is indistinguishable from its average returns over the period, 1.21% per month with a test statistic of 6.36. The bottom panel shows that the 6–2 strategy's abnormal returns relative to the three Fama-French factors and the 12–7 strategy is similarly essentially indistinguishable from its average returns over the period, 0.77% per month with a test statistic of 3.81.

The next two columns show results for the early and late halves of the data. They demonstrate that both strategies were more profitable over the second 41 years of the data than they were over the first 41 years. The 12–7 strategy yielded 1.45% per month, with a test statistic of 6.23, from January 1968 to December 2008, but only 0.98% per month, with a test statistic of 2.82, from January 1927 to December 1967, while the 6–2 strategy generated 1.06% per month, with a test statistic of 4.01, over the late sample, but only an insignificant 0.52% per month over the early sample (test statistic equal to 1.39). Despite the fact that the 6–2 strategy was more profitable during the late sample, and failed to generate significant returns during the early sample, it had a significant information ratio relative to the three Fama-French factors and the 12–7 strategy during the early sample, but not over the late sample. Over the early sample it contributed significantly to the investment opportunity set of an investor already trading the three Fama-French factors and the 12–7 momentum strategy, because it was relatively uncorrelated with the 12–7 strategy and provided a hedge on both HML and the market. Over the late sample it

Table 3.

Momentum strategy average returns and information ratios.

This table presents the average excess returns to momentum strategies constructed using intermediate horizon past performance ($MOM_{12,7}$) and recent past performance ($MOM_{6,2}$) and results of time series regressions of these strategies' returns on the three Fama-French factors and each other.

Independent variable	Full sample	Half sample		Quarter sample			
	Whole	Early	Late	First	Second	Third	Fourth
Panel A: Independent variable = $MOM_{12,7}$							
$E[r^e]$	1.21	0.98	1.45	1.15	0.81	1.43	1.46
	[5.80]	[2.82]	[6.23]	[1.75]	[3.60]	[4.68]	[4.18]
Intercept	1.21	1.11	1.17	1.47	0.46	1.06	1.26
	[6.36]	[3.58]	[5.50]	[2.55]	[2.01]	[3.66]	[4.02]
MKT	-0.03	-0.02	0.04	-0.05	0.09	0.11	-0.06
	[-0.81]	[-0.39]	[0.77]	[-0.56]	[1.42]	[1.64]	[-0.70]
SMB	0.02	0.12	-0.06	0.15	0.08	-0.03	-0.13
	[0.37]	[1.27]	[-0.89]	[1.02]	[0.70]	[-0.31]	[-1.36]
HML	-0.50	-0.69	-0.33	-0.75	-0.41	-0.18	-0.50
	[-9.12]	[-7.34]	[-4.38]	[-5.32]	[-4.08]	[-1.71]	[-4.40]
$MOM_{6,2}$	0.29	0.20	0.40	0.17	0.32	0.42	0.39
	[9.83]	[4.57]	[11.4]	[2.52]	[5.92]	[7.74]	[7.94]
Adj. R^2	0.225	0.238	0.239	0.250	0.161	0.215	0.261
Panel B: Independent variable = $MOM_{6,2}$							
$E[r^e]$	0.79	0.52	1.06	-0.19	1.22	1.10	1.02
	[3.45]	[1.39]	[4.01]	[-0.26]	[5.01]	[3.29]	[2.50]
Intercept	0.77	0.88	0.38	0.29	0.93	0.51	0.30
	[3.81]	[2.83]	[1.51]	[0.52]	[3.83]	[1.61]	[0.80]
MKT	-0.35	-0.40	-0.23	-0.48	-0.06	-0.11	-0.31
	[-9.17]	[-6.60]	[-4.18]	[-5.46]	[-0.86]	[-1.52]	[-3.29]
SMB	-0.23	-0.39	-0.01	-0.33	-0.30	-0.33	0.21
	[-3.75]	[-4.05]	[-0.17]	[-2.44]	[-2.51]	[-3.14]	[1.88]
HML	-0.25	-0.31	0.03	-0.37	0.19	0.03	0.12
	[-4.31]	[-3.18]	[0.32]	[-2.61]	[1.69]	[0.22]	[0.89]
$MOM_{12,7}$	0.32	0.20	0.52	0.15	0.39	0.48	0.54
	[9.83]	[4.57]	[11.4]	[2.52]	[5.92]	[7.74]	[7.94]
Adj. R^2	0.281	0.339	0.236	0.392	0.135	0.248	0.252

contributed little to the investment opportunity set of an investor already trading the three Fama-French factors and the 12–7 momentum strategy, despite the fact that it generated twice the absolute average returns over this period, because it covaried strongly with the 12–7 strategy and contributed little as an additional hedge on the Fama-French factors. The strong covariation between the 12–7 and 6–2 strategies in the second half of the data, even though these two strategies are constructed using completely disjoint past performance criteria, is surprising. The 12–7 strategy had a highly significant information ratio relative to the Fama-French factors and the 6–2 strategy over both halves of the data.

The last four columns show results for four equal 20.5-year subsamples. They show that the 12–7 strategy has a significant information ratio relative to the Fama-French factors and the 6–2 strategy in all four subsamples, while the 6–2 strategy has a significant information ratio relative to the Fama-French factors and the 12–7 strategy only in the immediate post-war sample, spanning July 1947 to December 1967. It also suggests that the strategies have become more correlated over time.

Fig. 4 presents similar, more nuanced results graphically. The figure shows the realized ten-year trailing performance of strategies based on intermediate horizon past performance ($\text{MOM}_{12,7}$, solid line) and recent past performance ($\text{MOM}_{6,2}$, dashed line) over time. The results are consistent with both the spanning tests of Table 3 and the rolling Fama-MacBeth regressions results depicted in Fig. 3.

Panel A, which depicts the strategies' realized trailing ten-year Sharpe ratios, shows again that the 6–2 strategy performed well in the 1950s and 1960s. The 6–2 generated negative returns, however, from the start of the sample (January 1927) through World War II. It also performed relatively poorly over the three and a half decades since Nasdaq's inclusion in CRSP, yielding a Sharpe ratio less than 60% of the Sharpe ratio on the 12–7 strategy. The 12–7 strategies, in contrast, performed well consistently over the entire sample, never yielding negative returns over any ten year sample.

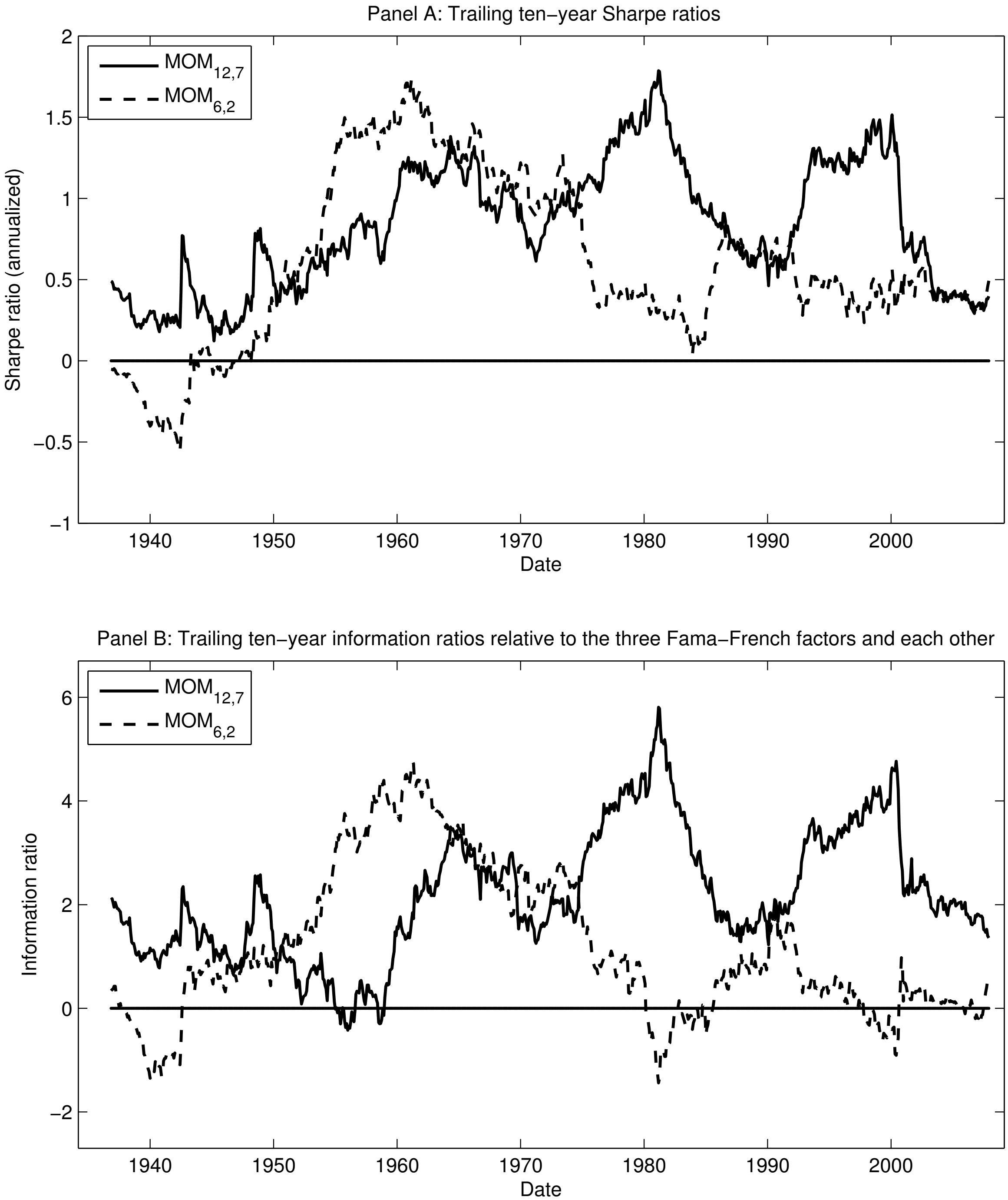

Figure 4. Momentum strategy trailing ten-year performance. Panel A shows the ten-year trailing Sharpe ratios of momentum strategies based on intermediate horizon past performance ($\mathrm{MOM}_{12,7}$, solid line) and recent past performance ($\mathrm{MOM}_{6,2}$, dashed line). Panel B depicts the strategies' information ratios relative to the three Fama-French factors and each other.

Panel B depicts the two strategies' information ratios relative to the three Fama-French factors and each other. The 12–7 strategy's information ratio has been significant in almost every ten year period beginning after 1950, while the 6–2 strategy's information ratio has generally only been significant over ten year periods ending in the mid-1950s to the mid-1970s.

Taken as a whole these spanning tests reinforce the conclusions drawn from the Fama-MacBeth tests. Intermediate past performance seems to contribute more than recent past performance to the profitability of conventional momentum strategies, especially over the last 40 years.

3.3. Double-sorted portfolios

This subsection presents results of time series regressions employing portfolios double-sorted on intermediate horizon and recent past returns. These test have great advantages. First, they show in perhaps the clearest way how recent returns correlate with expected returns and alphas after controlling for intermediate past returns. Univariate portfolio tests control for covariances but, unlike the Fama-MacBeth regressions, do not control for stock characteristics. The bivariate sorts permit controlling for covariances, by including factor returns as explanatory variables in the time series regressions, while simultaneously controlling for past performance characteristics, by constructing intermediate horizon past performance momentum strategies that are recent return neutral and recent past performance momentum strategies that are intermediate horizon return neutral.

The results of this procedure makes it clear that the covariance between recent-return and intermediate-return momentum strategies is not mechanical, i.e., not caused by a simple positive covariance between recent returns and intermediate past returns that results in the two strategies holding correlated portfolios. Recent-return strategies that are constructed to be intermediate-return neutral, even when constructed to hold completely disjoint positions from the intermediate-return momentum strategy, still covary surprisingly strongly with the intermediate-return strategy. This covariation is largely driven by the recent half of the data, January 1968 to December 2008.

Table 4 shows average returns and alphas for the 25 portfolios independently double-sorted on intermediate horizon and recent past performances. Because the autocorrelation in returns is weak, and $r_{12,7}$ and $r_{6,2}$ are thus relatively uncorrelated, the independent sort yields no thin cells. To maintain highly diversified portfolios I employ quintile sorts (again using NYSE breakpoints), instead of the decile sorts employed in the univariate portfolio tests. Portfolio returns are value-weighted, though equal-weighting the portfolios' returns yields qualitatively identical results.

Panel A of Table 4 again confirms the basic concisions of the previous two subsections. It shows that while both intermediate horizon and recent past performances are significantly related to returns going forward, recent past performance seems to have less predictive power. While the condition return spreads are generally significant in both directions, the magnitudes and significance of the spreads between intermediate horizon winners and losers are roughly twice those found between recent winners and losers.

It is also informative to directly compare recent winners that were intermediate horizon losers with recent losers that were intermediate horizon losers. Stocks that have risen the most over the past six months, but performed poorly over the first half of the preceding year, significantly under-perform stocks that have fallen the most over the past six months, but performed well over the first half of the preceding year. The difference in the returns to the intermediate horizon winners–recent losers portfolio and the recent winners–intermediate horizon losers portfolio is 0.52% per month, with a test statistic of 2.49. Relative to the Fama-French four-factor model, this outperformance is very similar: 0.52% per month with a test statistic of 2.48. These facts are difficult to reconcile with the traditional view

Table 4.
Performance of portfolios double-sorted on $r_{12,7}$ and $r_{6,2}$.

This table reports intercepts, in percent per month, from time series regressions employing the returns to portfolios double-sorted on intermediate and recent returns (IR and RR). The sorts employ NYSE break points, and portfolio returns are value-weighted. The sample covers January 1927 to December 2008.

	Estimate (percent per month)						Test statistics					
	IR1	IR2	IR3	IR4	IR5	5-1	IR1	IR2	IR3	IR4	IR5	5-1
Panel A: Excess returns (percent per month)												
RR1	-0.14	0.24	0.29	0.42	0.86	1.01	-0.45	0.81	1.11	1.72	3.04	5.31
RR2	0.16	0.52	0.50	0.79	0.88	0.72	0.60	2.20	2.34	3.57	3.87	4.21
RR3	0.09	0.38	0.68	0.80	1.12	1.03	0.37	1.88	3.31	4.33	5.34	5.90
RR4	0.13	0.51	0.59	0.85	1.06	0.93	0.55	2.57	3.20	4.81	5.18	5.04
RR5	0.35	0.65	0.90	0.93	1.29	0.94	1.48	3.15	4.53	4.85	5.90	5.34
5-1	0.49	0.41	0.61	0.50	0.42		2.39	1.95	3.11	2.74	2.04	
Panel B: Alphas relative to the CAPM												
RR1	-1.07	-0.61	-0.49	-0.30	0.04	1.10	-6.28	-3.82	-3.76	-2.45	0.25	5.83
RR2	-0.62	-0.18	-0.15	0.13	0.20	0.82	-4.56	-1.57	-1.70	1.26	1.90	4.81
RR3	-0.63	-0.23	0.05	0.23	0.49	1.12	-5.13	-2.59	0.60	3.04	5.05	6.47
RR4	-0.55	-0.08	0.01	0.30	0.46	1.01	-4.19	-0.94	0.21	4.39	4.50	5.50
RR5	-0.34	0.05	0.31	0.37	0.69	1.03	-2.88	0.50	3.24	3.83	5.41	5.89
5-1	0.73	0.67	0.80	0.67	0.65		3.72	3.37	4.28	3.79	3.31	
Panel C: Alphas relative to the three Fama-French factors												
RR1	-1.29	-0.81	-0.64	-0.41	-0.06	1.23	-8.54	-5.51	-5.32	-3.50	-0.46	6.60
RR2	-0.82	-0.35	-0.24	0.00	0.13	0.95	-6.74	-3.47	-2.80	0.02	1.30	5.73
RR3	-0.77	-0.33	-0.04	0.21	0.47	1.24	-6.76	-3.95	-0.52	2.83	4.76	7.26
RR4	-0.67	-0.17	-0.01	0.28	0.48	1.16	-5.42	-2.01	-0.22	4.20	4.73	6.55
RR5	-0.43	-0.01	0.29	0.38	0.77	1.20	-3.74	-0.14	3.01	3.95	6.38	7.24
5-1	0.86	0.80	0.93	0.80	0.83		4.52	4.11	5.09	4.59	4.37	
Panel D: Alphas relative to the four Fama-French factors												
RR1	-0.39	-0.04	-0.08	-0.03	0.13	0.52	-3.61	-0.36	-0.79	-0.31	0.91	3.04
RR2	-0.13	0.19	0.07	0.21	0.07	0.20	-1.43	2.49	0.89	2.23	0.68	1.41
RR3	-0.25	-0.03	0.17	0.11	0.18	0.43	-2.55	-0.43	2.20	1.46	1.93	2.99
RR4	-0.32	-0.02	-0.11	0.06	0.03	0.35	-2.66	-0.25	-1.53	1.01	0.34	2.30
RR5	-0.39	-0.11	-0.10	-0.05	0.10	0.49	-3.31	-0.97	-1.17	-0.57	1.08	3.36
5-1	-0.00	-0.06	-0.02	-0.01	-0.03		-0.00	-0.37	-0.15	-0.09	-0.16	
Panel E: Alphas relative to $MOM_{12,7}$												
RR1	0.72	0.87	0.78	0.72	1.02	0.30	2.49	3.07	3.07	2.91	3.56	2.04
RR2	0.94	1.09	0.88	1.09	0.96	0.02	3.93	5.01	4.26	4.94	4.13	0.17
RR3	0.78	0.81	1.01	0.92	1.06	0.28	3.58	4.19	5.08	4.93	4.96	2.33
RR4	0.81	0.93	0.81	0.95	0.98	0.18	3.77	4.99	4.43	5.32	4.72	1.32
RR5	0.90	1.05	1.05	0.99	1.07	0.17	4.12	5.25	5.23	5.09	4.90	1.43
5-1	0.18	0.18	0.26	0.27	0.05		0.90	0.84	1.40	1.49	0.24	
panel F: alphas relative to the three Fama-French factors plus $MOM_{12,7}$												
RR1	-0.63	-0.48	-0.43	-0.44	-0.31	0.32	-4.83	-3.29	-3.58	-3.63	-2.30	2.10
RR2	-0.23	-0.00	-0.09	-0.01	-0.17	0.06	-2.27	-0.04	-1.08	-0.13	-1.74	0.46
RR3	-0.23	-0.11	0.04	0.07	0.02	0.25	-2.39	-1.30	0.53	0.90	0.25	2.04
RR4	-0.13	0.07	-0.02	0.12	0.08	0.21	-1.22	0.84	-0.23	1.86	0.84	1.54
RR5	-0.02	0.20	0.19	0.20	0.22	0.24	-0.19	1.88	1.88	2.04	2.19	2.06
5-1	0.61	0.68	0.62	0.64	0.54		3.17	3.41	3.37	3.60	2.80	

of momentum as a short-run autocorrelation in returns.

Panels B and C show that the capital asset pricing model (CAPM) and the Fama-French three-factor model both exacerbate the pricing errors of the spread portfolios in each direction. Panel D shows that the Fama-French four factor model significantly improves the portfolio pricing errors, and does a good job pricing the recent past performance momentum strategies, but fails to price the intermediate horizon momentum strategies. Panel E shows that recent past performance momentum strategies have alphas close to zero when they are regressed on the intermediate horizon past performance momentum strategy $\text{MOM}_{12,7}$, though this factor performs poorly pricing the underlying double-sorted portfolios individually. Panel F shows, somewhat surprisingly, that adding $\text{MOM}_{12,7}$ as an explanatory variable to the three Fama-French factors improves the pricing of the recent past performance momentum strategies, though these strategies' alphas relative to these four factors are still highly significant.

Our previous results suggest, however, that $\text{MOM}_{12,7}$ can do better pricing the double-sorted portfolios over the second half of the sample. Table 1 shows that the significance of the difference in the Fama-MacBeth regression coefficients on intermediate horizon and recent past performance was greater in the more recent 41 year subsample. Table 3 shows that $\text{MOM}_{6,2}$ has a significant information ratio relative to the three Fama-French factors and $\text{MOM}_{12,7}$ in the early sample, but not the late sample. These facts lead to an analysis of the late sample results of the bivariate sorts. Table 5 repeats the analysis of Table 4 over the second half of the sample, spanning January 1968 to December 2008.

Consistent with the earlier results, over this period the difference in performance between momentum strategies based on intermediate horizon past performance and recent past performance is more pronounced (Panel A). While the conditional intermediate horizon past performance momentum strategies all generate highly significant returns, a

Table 5.

Late sample performance of portfolios double-sorted on $r_{12,7}$ and $r_{6,2}$.

This table reports intercepts, in percent per month, from time series regressions employing the returns to portfolios double-sorted on intermediate and recent returns (IR and RR). The sorts employ NYSE break points, and portfolio returns are value-weighted. The sample covers January 1968 to December 2008.

	Estimate (percent per month)						Test statistics					
	IR1	IR2	IR3	IR4	IR5	5-1	IR1	IR2	IR3	IR4	IR5	5-1
Panel A: Excess returns (percent per month)												
RR1	-0.71	-0.10	0.13	0.09	0.39	1.10	-2.00	-0.32	0.45	0.32	1.24	5.19
RR2	-0.21	0.37	0.38	0.46	0.55	0.76	-0.75	1.53	1.67	2.10	2.13	3.65
RR3	-0.09	0.23	0.40	0.48	0.88	0.97	-0.31	1.11	2.06	2.37	3.68	4.34
RR4	-0.22	0.13	0.32	0.54	0.72	0.94	-0.93	0.62	1.57	2.71	2.90	4.69
RR5	-0.29	0.33	0.59	0.66	1.06	1.35	-1.10	1.45	2.51	2.81	3.63	6.69
5-1	0.42	0.42	0.46	0.57	0.67		1.65	1.87	1.98	2.64	2.76	
Panel B: Alphas relative to the CAPM												
RR1	-1.17	-0.51	-0.26	-0.30	-0.07	1.10	-5.45	-2.83	-1.68	-2.10	-0.44	5.19
RR2	-0.58	0.03	0.06	0.14	0.17	0.76	-3.57	0.26	0.51	1.36	1.44	3.64
RR3	-0.45	-0.06	0.12	0.19	0.54	1.00	-2.85	-0.51	1.28	1.92	4.43	4.46
RR4	-0.56	-0.16	0.02	0.25	0.36	0.92	-4.19	-1.48	0.18	2.66	3.07	4.56
RR5	-0.66	-0.00	0.26	0.33	0.66	1.33	-4.78	-0.01	2.14	2.63	3.98	6.57
5-1	0.51	0.51	0.51	0.63	0.73		2.06	2.28	2.22	2.93	3.05	
Panel C: Alphas relative to the three Fama-French factors												
RR1	-1.29	-0.70	-0.37	-0.38	-0.07	1.23	-6.18	-3.92	-2.45	-2.64	-0.44	5.72
RR2	-0.75	-0.16	-0.06	0.03	0.12	0.87	-4.62	-1.25	-0.55	0.25	1.01	4.15
RR3	-0.66	-0.21	0.01	0.08	0.50	1.16	-4.24	-1.95	0.16	0.80	4.01	5.17
RR4	-0.68	-0.34	-0.07	0.16	0.40	1.08	-5.10	-3.28	-0.82	1.75	3.38	5.35
RR5	-0.76	-0.07	0.20	0.27	0.78	1.54	-5.76	-0.66	1.65	2.08	4.92	7.67
5-1	0.54	0.63	0.57	0.65	0.85		2.13	2.78	2.43	2.94	3.48	
Panel D: Alphas relative to the four Fama-French factors												
RR1	-0.40	0.04	0.15	0.01	0.19	0.59	-3.00	0.36	1.25	0.04	1.32	3.20
RR2	-0.12	0.29	0.24	0.16	0.07	0.20	-1.05	2.94	2.22	1.56	0.59	1.13
RR3	-0.14	0.03	0.13	0.01	0.29	0.43	-1.11	0.30	1.44	0.12	2.38	2.32
RR4	-0.41	-0.23	-0.16	-0.03	0.04	0.44	-3.19	-2.19	-1.78	-0.32	0.37	2.61
RR5	-0.78	-0.21	-0.18	-0.13	0.14	0.92	-5.72	-1.90	-1.81	-1.20	1.27	5.40
5-1	-0.38	-0.25	-0.33	-0.14	-0.06		-1.96	-1.54	-1.95	-0.79	-0.30	
Panel E: Alphas relative to $\mathrm{MOM}_{12,7}$												
RR1	0.08	0.46	0.42	0.26	0.27	0.19	0.24	1.52	1.47	0.92	0.82	1.17
RR2	0.43	0.74	0.61	0.50	0.28	-0.14	1.58	3.08	2.66	2.19	1.08	-0.93
RR3	0.56	0.51	0.50	0.45	0.52	-0.05	2.14	2.40	2.50	2.13	2.14	-0.29
RR4	0.27	0.40	0.35	0.44	0.29	0.02	1.12	1.89	1.63	2.13	1.18	0.17
RR5	-0.01	0.41	0.38	0.44	0.38	0.40	-0.05	1.75	1.56	1.82	1.36	2.90
5-1	-0.09	-0.05	-0.04	0.18	0.12		-0.38	-0.23	-0.20	0.83	0.49	
Panel F: Alphas relative to the three Fama-French factors plus $\mathrm{MOM}_{12,7}$												
RR1	-0.34	-0.05	-0.03	-0.17	-0.17	0.17	-2.02	-0.33	-0.17	-1.15	-1.10	1.05
RR2	-0.01	0.25	0.20	0.06	-0.18	-0.17	-0.07	2.16	1.72	0.54	-1.51	-1.08
RR3	0.08	0.09	0.12	0.02	0.07	-0.01	0.62	0.84	1.29	0.18	0.61	-0.04
RR4	-0.10	-0.06	-0.05	0.03	-0.07	0.04	-0.94	-0.55	-0.51	0.29	-0.67	0.24
RR5	-0.42	0.03	-0.05	0.00	0.05	0.47	-3.26	0.29	-0.40	0.02	0.36	3.34
5-1	-0.08	0.09	-0.02	0.17	0.22		-0.32	0.39	-0.10	0.79	0.92	

GRS (Gibbons, Ross, and Shanken, 1989) test fails to reject the hypothesis that the excess returns to conditional recent recent past performance momentum strategies are jointly zero ($F_{5,487} = 1.68$, for a p-value of 13.8%). As a result, stocks that have risen the most over the past six months but performed poorly over the first half of the preceding year under-perform stocks that have fallen the most over the past six months but performed well over the second half of the preceding year by 0.68% per month, with a test statistic of 2.99. Relative to the Fama-French four-factor model, this outperformance is 0.97% per month with a test statistic of 4.26.

Panels B and C again show that the CAPM and the Fama-French three-factor model both exacerbate the pricing errors of the spread portfolios in each direction. Panel D shows that the Fama-French four-factor model improves the portfolio pricing errors, but tends to overprice the recent past performance momentum strategies, which all have negative four-factor alphas, and underprice the intermediate horizon momentum strategies, which all have positive four-factor alphas.

Panels E and F show that $\text{MOM}_{12,7}$ does a good job, especially in conjunction with the three Fama-French factors, of pricing the 25 test portfolios over the late half of the sample. While the root mean squared average excess return of the 25 portfolios is 0.48% per month, it is only 0.15% per month relative to the three Fama-French factors plus $\text{MOM}_{12,7}$.

Table 6 shows the average returns to the spread portfolios in each direction, and full results from time series regressions of these strategies' returns onto the three Fama-French factors and $\text{MOM}_{12,7}$. The root mean squared average excess return of the five intermediate horizon past performance momentum strategies constructed within recent past performance quintiles is 1.04% per month, while that of the five recent past performance momentum strategies constructed with intermediate horizon past performance quintiles is only half as large, 0.52% per month. Unsurprisingly, the three Fama-French factors plus $\text{MOM}_{12,7}$ do a good job pricing the conditional intermediate horizon past performance momentum

Table 6.
Performance of conditional momentum strategies.

This table shows the average returns to the five winner-minus-loser portfolios in each direction from the double sort on recent and intermediate horizon past performances ($r_{6,2}$ and $r_{12,7}$), and results from time series regressions employing these strategies' returns. The sample covers January 1968 to December 2008.

	$MOM_{12,7}$ conditioned on recent past performance					$MOM_{6,2}$ conditioned on intermediate horizon past performance				
	$r_{6,2}$ quintile					$r_{12,7}$ quintile				
	(L)	(2)	(3)	(4)	(W)	(L)	(2)	(3)	(4)	(W)
$E[r^e]$	1.10	0.76	0.97	0.94	1.35	0.42	0.42	0.46	0.57	0.67
	[5.19]	[3.65]	[4.34]	[4.69]	[6.69]	[1.65]	[1.87]	[1.98]	[2.64]	[2.76]
α	0.17	-0.17	-0.01	0.04	0.47	-0.08	0.09	-0.02	0.17	0.22
	[1.05]	[-1.08]	[-0.04]	[0.24]	[3.34]	[-0.32]	[0.39]	[-0.10]	[0.79]	[0.92]
MKT	0.01	0.02	-0.07	0.06	0.02	-0.23	-0.25	-0.13	-0.16	-0.23
	[0.37]	[0.69]	[-1.88]	[1.76]	[0.59]	[-4.14]	[-4.93]	[-2.48]	[-3.29]	[-4.22]
SMB	-0.13	-0.11	-0.12	-0.04	0.01	-0.06	-0.09	-0.08	0.05	0.07
	[-2.53]	[-2.16]	[-2.40]	[-0.80]	[0.22]	[-0.84]	[-1.37]	[-1.13]	[0.69]	[0.99]
HML	0.05	0.06	0.00	-0.04	-0.13	0.11	-0.07	0.05	0.08	-0.07
	[0.93]	[1.12]	[0.08]	[-0.75]	[-2.62]	[1.29]	[-0.87]	[0.66]	[1.06]	[-0.83]
$MOM_{12,7}$	0.63	0.63	0.70	0.63	0.64	0.37	0.32	0.36	0.28	0.38
	[21.0]	[21.4]	[23.4]	[23.2]	[24.8]	[8.03]	[7.85]	[8.33]	[6.95]	[8.55]

strategies. The root mean squared pricing error of these strategies relative to the three Fama-French factors plus $MOM_{12,7}$ is only 0.24% per month. More surprisingly, the three Fama-French factors plus $MOM_{12,7}$ also do a good job pricing the conditional recent past performance momentum strategies. The root mean squared pricing error of these strategies relative to the three Fama-French factors plus $MOM_{12,7}$ is only 0.14% per month, and a GRS test fails to reject the hypothesis that the alphas of the five strategies relative to the three Fama-French factors and $MOM_{12,7}$ are jointly zero ($F_{5,483} = 0.51$, for a p-value of 80.0%).

The reason $MOM_{12,7}$ helps price the recent past performance momentum strategies is that these strategies load surprisingly heavily on the factor. The average loading of these strategies on the intermediate past performance momentum factor exceeds a third, more than half the average load of the conditional intermediate past performance momentum strategies. These loadings are observed despite the fact that the conditional recent past performance momentum strategies are explicitly constructed so as to be neutral with respect to the intermediate past performance characteristic. These loadings are observed even on the 6–2 strategies built within the middle three intermediate horizon past performance quintiles, strategies that are by construction completely disjointed from $\mathrm{MOM}_{12,7}$, in the sense that these conditional 6–2 strategies take no positions, either long or short, in any stock held either long or short by the 12–7 strategy.

Fig. 5 provides a further investigation of how recent past performance momentum strategies load on intermediate horizon past performance momentum strategies over time, even when the recent past performance strategy is explicitly constructed such that it is neutral with respect to the intermediate past performance characteristic, and vice versa. Specifically, the figure shows the slope coefficient on $\mathrm{MOM}_{12,7|6,2}$ from rolling ten-year regressions of $\mathrm{MOM}_{6,2|12,7}$ on $\mathrm{MOM}_{12,7|6,2}$ and the three Fama-French factors, where $\mathrm{MOM}_{12,7|6,2}$ (respectively, $\mathrm{MOM}_{6,2|12,7}$) holds each of the five conditional intermediate horizon (respectively, recent) past performance momentum strategies in equal proportion.

The figure shows that, while $\mathrm{MOM}_{6,2|12,7}$ loads negatively on $\mathrm{MOM}_{12,7|6,2}$ in the very beginning of the sample, it loads positively on $\mathrm{MOM}_{12,7|6,2}$ in every ten-year subsample ending after the mid-1940's, and these loadings are generally significant, even though these subsamples are relatively short. The mean ten-year loading over the entire sample exceeds 0.25, and the test statistics in these regressions are very close to ten times the magnitude of the slope coefficients. These significant comovements are observed despite the fact, again, that the two strategies are designed, by construction, to be neutral with respect to the characteristic used in the sort employed in the other strategy's formation.

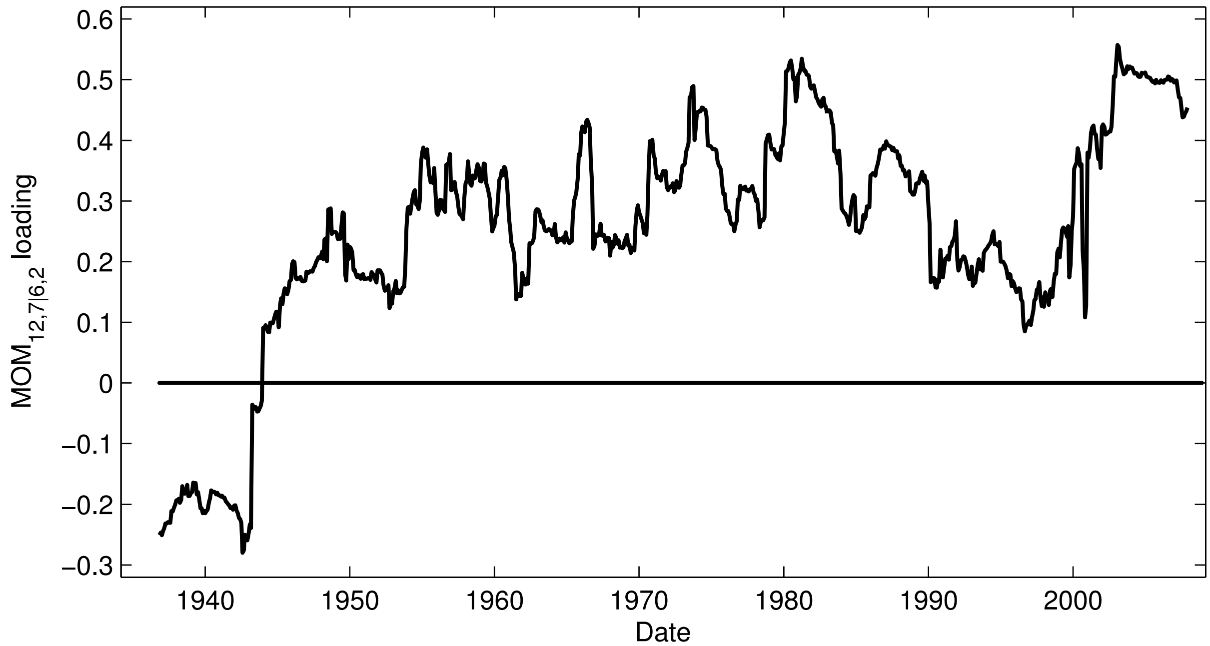

Fig. 5. Trailing ten-year loadings of $\mathrm{MOM}_{6,2|12,7}$ on $\mathrm{MOM}_{12,7|6,2}$. This figure shows rolling ten-year slope coefficient on $\mathrm{MOM}_{12,7|6,2}$ from time series regressions of $\mathrm{MOM}_{6,2|12,7}$ on $\mathrm{MOM}_{12,7|6,2}$ and the three Fama-French factors.

4. The role of size

It is generally accepted that momentum is concentrated in small stocks. This suggests that my analysis should include an investigation of the effects of firm size. I consequently consider the performance of momentum strategies constructed within market capitalization quintiles. The results suggest that the disparity in the power of intermediate horizon and recent past performance to predict returns is especially acute for large stocks.

Panel A of Table 7 shows time series average characteristics of the size portfolios, which are constructed using NYSE breaks. Panel B reports the average monthly returns to momentum strategies that control for firm size. These strategies consist of winners-minus-losers, based on a quintile sort on past performance, constructed within size quintiles, and are denoted by $\mathrm{MOM}^{i}_{n,m}$, where winners and losers are based on cumulative

Table 7.
Momentum strategy performance by size quintile.

This table reports the average returns to momentum strategies based on recent and intermediate horizon past performance, constructed within size quintiles [$\text{MOM}^i_{n,m}$, where winners and losers are defined using a quintile sort on cumulative returns from n to m months (inclusive) prior to portfolio formation, and the portfolios contain stocks only from size quintile i], and the abnormal returns to these strategies relative to the three Fama-French factors and each other. Portfolio break points based on NYSE stocks only. The full sample covers January 1927 through December 2008. The late sample covers January 1968 through December 2008.

	Size portfolio				
	(Small)	(2)	(3)	(4)	(Large)
Panel A: Size portfolio time series average characteristics					
Number of firms	1756	643	473	379	331
Percent of firms	37.9	18.5	15.8	14.3	13.5
Total cap. (billions of dollars)	54.5	96.7	171	343	2,454
Percent of capitalization	1.7	3.0	5.5	12.0	77.8
Ave. cap. (millions of dollars)	18.3	81.5	203	535	4,061
Panel B: Portfolio average excess returns, full sample					
$\text{MOM}^i_{12,7}$	0.87	0.89	1.06	0.91	0.82
	[5.36]	[6.76]	[6.90]	[5.30]	[4.61]
$\text{MOM}^i_{6,2}$	0.58	0.81	0.61	0.60	0.31
	[3.31]	[4.69]	[3.18]	[3.25]	[1.64]
Panel C: αs relative to the three Fama-French factors and each other, full sample					
$\text{MOM}^i_{12,7}$	0.82	0.88	1.16	0.97	0.91
	[5.24]	[6.95]	[8.03]	[6.37]	[5.40]
$\text{MOM}^i_{6,2}$	0.65	0.86	0.73	0.60	0.48
	[4.10]	[5.47]	[4.18]	[3.60]	[2.69]
Panel D: Portfolio average excess returns, late sample					
$\text{MOM}^i_{12,7}$	1.19	1.11	1.16	0.95	0.88
	[7.80]	[7.66]	[7.08]	[5.16]	[4.10]
$\text{MOM}^i_{6,2}$	1.22	1.16	0.80	0.63	0.31
	[6.26]	[5.84]	[3.88]	[2.89]	[1.37]
Panel E: αs relative to the three Fama-French factors and each other, late sample					
$\text{MOM}^i_{12,7}$	0.78	0.77	1.02	0.84	0.91
	[5.82]	[5.71]	[6.48]	[4.97]	[4.47]
$\text{MOM}^i_{6,2}$	0.44	0.51	0.38	0.17	0.04
	[2.50]	[2.70]	[1.83]	[0.82]	[0.17]

returns from n to m months (inclusive) prior to portfolio formation and the superscript i identifies the size quintile. Sorting on intermediate past performance generates larger, more significant return spreads across size portfolios. The root mean squared return spread between intermediate horizon winners and losers across size quintiles is 0.91% per month. For recent winners and losers it is 0.60% per month. This disparity in performance is especially pronounced for large stocks, which make up more than three quarters of the market by capitalization. Within the largest stocks the strategy based on intermediate past performance generates annual excess returns of 10%, while the strategy based on recent past performance fails to generate statistically significant excess returns.

Panel C shows the strategies' abnormal returns relative to the three Fama-French factors and each other. These abnormal returns are always significant, though always larger and more significant for the strategies based on intermediate past performance. The disparity in the significance of the abnormal returns is again especially pronounced for the large capitalization strategies.

Panels D and E duplicate the results of Panels B and C in the second half of the sample, January 1968 to December 2008, and show similar, though somewhat stronger, results. In particular, while the information ratios of the intermediate horizon past performance strategies are always highly significant relative to the three Fama-French factors and the recent past performance strategies, the recent past performance strategies' four-factor alphas are significant only in the two smallest size quintiles, which make up less than 5% of the market by capitalization.

Equal-weighted strategies perform almost identically to their value-weighted counterparts after controlling for size, with one striking difference: the poor performance of the equal-weighted micro cap momentum strategies. Value-weighted $\text{MOM}_{6,2}^{\text{small}}$ returns 0.58% per month, while equal-weighted $\text{MOM}_{6,2}^{\text{small}}$ returns only 0.15% per month. This results because the smallest 10% of stocks, which make up only 0.06% of the market by capitalization, exhibit no momentum. Interestingly, while equal-weighting the micro-cap momentum strategy based on intermediate horizon past performance also results in a performance deterioration relative to its value-weighted performance, it is less marked than it is for the strategies based on recent past performance. Value-weighted $\text{MOM}^{\text{small}}_{12,7}$ returns 0.87% per month, while equal-weighted $\text{MOM}^{\text{small}}_{12,7}$ returns 0.61% per month.

5. Other markets

The results presented in the previous sections are not unique to the US stock market. My main results hold for momentum strategies that employ alternative assets, even when the returns to these alternative momentum strategies are essentially uncorrelated with the returns to momentum strategies constructed within the cross section of US equities. To show this I construct momentum strategies using industries, investment styles (i.e., size and book-to-market sorted portfolios), foreign markets (i.e., country equity indices), commodities, and foreign currencies. Previous papers show the existence of momentum in all of these markets. For more on momentum in other markets see, for example, Moskowitz and Grinblatt (1999) and Asness, Porter and Stevens (2000) (industries), Lewellen (2002) and Chen and De Bondt (2004) (style), Asness, Liew and Stevens (1997), Bhojraj and Swaminathan (2006) and Asness, Moskowitz and Pedersen (2008) (international indicies), Gorton, Hayashi and Rouwenhorst (2007) and Asness, Moskowitz and Pedersen (2008) (commodities), and Bhojraj and Swaminathan (2006), Lustig, Roussanov and Verdelhan (2008) and Asness, Moskowitz, and Pedersen (2008) (foreign currencies). My interest in these markets derives from their ability to provide additional tests of the hypothesis that momentum derives primarily from intermediate horizon, not recent, past performance.

While each of these markets does not provide a completely independent test of the results observed in the cross section of US equities, taken together they provide compelling confirmation of the results seen there. In particular, the results that employ industry and style momentum may not represent truly independent tests, because these strategies, while distinct from the "conventional" momentum, have returns that are highly correlated with the returns to conventional momentum. Country and commodity momentum are only weakly correlated with conventional momentum, however, and currency momentum is uncorrelated with conventional momentum. The results that employ momentum strategies constructed in these markets consequently represent essentially independent tests. In all of these markets, intermediate horizon momentum strategies generate large, significant returns that cannot be explained by the returns to strategies based on recent past performance, while the returns to strategies based on recent past performance generate smaller returns, which are always insignificant relative to the returns to strategies based on intermediate horizon past performance.

Finally, in addition to providing confirmation of the conclusions drawn from the cross section of US equities, results observed in these markets address several robustness issues. In particular, the fact that intermediate horizon past performance drives momentum in all these markets means that the results are not driven by the 12-month effect of Heston and Sadka (2008), which does not exist in international equity indices, commodity markets, or foreign currency markets. It also suggests that the results are unrelated to calendar effects, as the poor January performance observed in conventional momentum strategies is absent from strategies that trade investment styles, foreign markets, commodities, and currencies.

5.1. Strategy formation

I construct momentum strategies across markets employing a consistent methodology. The only difference in these five sets of alternative momentum strategies are the assets included in the investment opportunity set. The assets employed are (1) the Fama-French 49 industries; (2) 25 size and book-to-market sorted portfolios; (3) 23 tradable MSCI developed-market country indices; (4) futures on 31 commodities; and (5) 19 currencies.

In each market, strategies are formed by sorting on recent and intermediate horizon past performance ($r_{12,7}$ and $r_{6,2}$, respectively). While these markets do not generally exhibit the short-term reversals observed in individual stock data, and it is consequently not necessary to skip a month when forming the momentum strategies based on recent past performance, doing so has no material impact on the results and allows for direct comparison with those observed in the cross section of US equities. Because each of these alternative momentum strategies is built from a relatively small set of assets, I employ a tertile sort on past performance. That is, winners are defined as the top 30% of past performers, and losers are the bottom 30%. Using a quintile sort, or the rank-weighting procedure employed by Asness, Moskowitz, and Pedersen (2008), yields qualitatively identical results. Strategy returns are equal-weighted, though when the underlying assets are themselves portfolios (industries, investment styles, or country indices) these portfolios' returns are value-weighted.

5.2. Industry momentum

Industry momentum strategies generate significant returns and load heavily on conventional momentum measures constructed using the entire cross section of US stock returns such as UMD (Moskowitz and Grinblatt, 1999). I construct industry momentum strategies based on intermediate horizon and recent past performance using the Fama-French 49 industries. Table 8 reports these strategies' average monthly returns, as well as the results of time series regressions of these strategies' returns on UMD and each other.

Specifications 1 and 4 show the average monthly returns to the 12–7 and 6–2 strategies, respectively. The 12–7 strategy generates 0.56% per month, roughly twice the 0.29% per month that the 6–2 strategy yields. The two strategies' realized annual Sharpe ratios over

Table 8.
Industry momentum strategy spanning tests.

This table shows the results of time series regressions employing the returns to industry momentum strategies constructed using past performance over different horizons. $\text{MOM}_{n,m}^{\text{indus}}$ is the returns to the winner-minus-loser portfolio (tertiles), where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers January 1927 through December 2008.

Independent variable	$\text{MOM}_{12,7}^{\text{indus}}$ as dependent variable			$\text{MOM}_{6,2}^{\text{indus}}$ as dependent variable		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.56	0.18	0.46	0.27	-0.17	0.07
	[4.83]	[1.93]	[4.26]	[2.33]	[-1.90]	[0.62]
UMD		0.50			0.58	
		[26.0]			[31.6]	
$\text{MOM}_{6,2}^{\text{indus}}$			0.34			
			[12.2]			
$\text{MOM}_{12,7}^{\text{indus}}$						0.38
						[12.2]
Adj. R^2		0.407	0.130		0.504	0.130

the sample are 0.53 and 0.26, respectively. Specifications 2 and 5 show that both strategies have large, significant loadings on UMD, which explain most of these strategies' abnormal returns. The 12–7 strategy, however, still generates marginally abnormal returns relative to UMD (0.18% per month with a test statistic of 1.93), while the 6–2 strategy's abnormal returns relative to UMD are negative and marginally significant (-0.17% per month with a test statistic of -1.90). Specifications 3 and 6 show that the 12–7 strategy has a large, highly significant information ratio relative to the 6–2 strategy, while the 6–2 strategy has a completely insignificant information ratio relative to the 12–7 strategy.

While there is very little 6–2 industry momentum, industries do exhibit momentum at very short (one month) horizons, consistent with the results of Moskowitz and Grinblatt (1999). Last month's winning industries outperform losing industries by 0.38% per month, and this outperformance is significant, with a test statistic of 3.52. This short horizon industry momentum is largely driven by intra-industry lead lag effects, like those analyzed in Hou (2007). The smallest 20% of firms in last month's winning industries outperform the smallest firms in losing industries by 0.95% per month (test statistic equal to 6.08). Even so, the results of Table 8 are robust to including last month's returns in the short horizon strategy's past performance evaluation period. The strategy based on performance over the entire preceding six months generates 0.43% per month (test statistic equal to 3.43), roughly the same as the returns to the strategy based on last month's returns alone. That is, including past performance in months two to six prior in the selection criteria does not improve the performance of the very short horizon industry momentum strategy. While the 6-1 strategy performs better than the 6–2 strategy, it does not contain significant information relative to the 12–7 strategy, which itself has a large information ratio relative to the 6-1 strategy. The 6-1 strategy generates 0.21% per month relative to the 12–7 strategy, with a test statistic of 1.79. The 12–7 strategy generates 0.42% per month relative to the 6-1 strategy, with a test statistic of 3.83.

5.3. Style momentum

Investment styles, i.e., strategies that hold stocks based on valuation ratios, market capitalization, or both, exhibit significant momentum. Lewellen (2002) shows that these strategies are distinct from industry momentum strategies, which cannot explain their profits (see also Chen and De Bondt, 2004). Table 9 reports results from tests that employ style momentum strategies, constructed from 25 value-weighted size and book-to-market sorted portfolios. The table reports average monthly returns to strategies based on intermediate horizon and recent past performances, as well as time series regressions of these strategies' returns on UMD and each other.

The results presented in Table 9 are similar to those observed in Table 8. Specifications 1 and 4 show the average monthly returns to the 12–7 and 6–2 strategies, respectively.

Table 9.
Style momentum strategy spanning tests.

This table shows the results of time series regressions employing the returns to investment style momentum strategies constructed using past performance over different horizons. $\mathrm{MOM}^{\mathrm{style}}_{n,m}$ is the returns to the winner-minus-loser portfolio (tertiles), where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers July 1927 through December 2008.

Independent variable	$\mathrm{MOM}^{\mathrm{style}}_{12,7}$ as dependent variable			$\mathrm{MOM}^{\mathrm{style}}_{6,2}$ as dependent variable		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.43	0.13	0.43	0.14	-0.17	0.13
	[3.86]	[1.34]	[3.82]	[1.11]	[-1.54]	[0.97]
UMD		0.39			0.41	
		[19.4]			[17.3]	
$\mathrm{MOM}^{\mathrm{style}}_{6,2}$			0.03			
			[1.05]			
$\mathrm{MOM}^{\mathrm{style}}_{12,7}$						0.04
						[1.05]
Adj. R^2		0.278	0.0		0.265	0.0

The 12–7 strategy generates large, significant, average returns (0.43% per month, with a test statistic of 3.86), while the 6–2 fails to generate statistically significant returns (0.14% per month, with a test statistic of 1.11). The two strategies' realized annual Sharpe ratios over the sample are 0.43 and 0.12, respectively. Specifications 2 and 5 show that the style strategies, like the industry strategies, have large, significant UMD loadings. Moreover, the loading on the 6–2 strategy is even higher than that on the 12–7 strategy, despite the fact that the 6–2 strategy fails to generate abnormal average returns. Specifications 3 and 6 show that the 12–7 strategy again has a large, highly significant information ratio relative to the 6–2 strategy, while the 6–2 strategy has an insignificant information ratio relative to the 12–7 strategy. In these regressions the two strategies barely load on each other. Their returns are only 3.4% correlated. This contrasts sharply with momentum strategies constructed in the cross section of US equities or using industries, there the correlations

between the 12–7 and 6–2 strategies are 40.0% and 36.0%, respectively.

Again, while styles exhibit no 6–2 momentum, like industries they do exhibit significant momentum at very short horizons. Last month's winning styles outperform losing styles by 0.50% per month, with a test statistic of 4.37. The results of Table 9 are robust, however, to including last month's returns in the short horizon strategy's past performance evaluation period. The 6-1 strategy does not contain significant information relative to the 12–7 strategy, while the 12–7 strategy has a large information ratio relative to the 6-1 strategy. The 6-1 strategy generates 0.18% per month relative to the 12–7 strategy, with a test statistic of 1.41. The 12–7 strategy generates 0.43% per month relative to the 6-1 strategy, with a test statistic of 3.80. Moreover, the strategy based on performance over the entire preceding six months generates only 0.20% per month (test statistic equal to 1.55), much less than the strategy based on last month's returns alone. That is, including past performance in months two to six prior in the selection criteria greatly reduces the performance of the very short horizon industry momentum strategy.

5.4. Country index momentum

Country-level stock indices also exhibit significant momentum (Asness, Liew, and Stevens, 1997). Momentum strategies that buy and sell country indices, even those that exclude the US market, have statistically significant loadings on UMD despite the fact that UMD is constructed entirely within the cross section of US equities. These UMD loadings are small, however, and generally explain less than 10% of the variation in the international momentum strategies' returns. International momentum strategies consequently provide a largely independent test of the results established in this paper.

I construct country index momentum strategies using the dollar returns to 23 developed country markets (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, Australia, Hong Kong, Japan, New Zealand, Singapore, Canada, and the US). These data are largely constructed using Barra's MSCI Global Investable Market Indices. I obtain 7,009 country-month observations directly from Barra. These data are augmented using the country returns on Ken French's website, which are also constructed using MSCI data. In cases in which the French data include observations missing from the data obtained from Barra, these observations are included in the merged data. The two data sets are 98.6% correlated where they overlap (4,944 observations). The French data contribute an additional 2,136 observations. An additional three hundered observations are taken from the international equity index data employed by Asness, Moskowitz, and Pedersen (2008), which is 89.9% correlated with the Barra and French data where they overlap (8,315 observations). Returns for 12 markets are available back to January 1970, and for all 23 markets starting in December 1988.

Ideally the returns would be hedged against currency fluctuations, to disentangle momentum in the equity indices from momentum in the currencies in which they are denominated, but I can only construct hedged country index returns for sixteen countries from November 1984 through August 2007. Analysis of the hedged and unhedged country index momentum strategies on this sample, however, provides compelling evidence that the performance of the unhedged strategies is due to momentum in the indices themselves, and not to currency momentum.

Table 10 shows the results of tests employing returns to the 12–7 and 6–2 strategies. These results are consistent with those observed in the cross section of US equities, industries and styles. Specifications 1 and 4 report the average monthly returns to the 12–7 and 6–2 strategies, respectively. The 12–7 strategy generates 0.99% per month, more than twice the 0.46% per month that the 6–2 strategy yields. The two strategies' realized annual Sharpe ratios over the sample are 0.86 and 0.38, respectively. Specifications 2 and 5 show that both strategies have significant loadings on UMD, consistent with the

Table 10.
International momentum strategy spanning tests.

This table shows the results of time series regressions employing the returns to international index momentum strategies constructed using past performance over different horizons. $\text{MOM}_{n,m}^{\text{int'l}}$ is the returns to the winner-minus-loser portfolio (tertiles), where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers January 1971 through November 2008.

Independent variables	$\text{MOM}_{12,7}^{\text{int'l}}$ as dependent variable			$\text{MOM}_{6,2}^{\text{int'l}}$ as dependent variable		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.99	0.85	0.84	0.46	0.18	0.07
	[5.31]	[4.43]	[4.81]	[2.22]	[0.90]	[0.37]
UMD		0.18			0.31	
		[4.06]			[6.49]	
$\text{MOM}_{6,2}^{\text{int'l}}$			0.31			
			[7.93]			
$\text{MOM}_{12,7}^{\text{int'l}}$						0.39
						[7.93]
Adj. R^2		0.033	0.120		0.083	0.120

results of Asness, Moskowitz, and Pedersen (2008), though the 6–2 strategy's loading on UMD is almost twice the 12–7 strategy's loading, even though it generates less than half the abnormal returns. Specifications 3 and 6 show that the 12–7 strategy has a large, highly significant information ratio relative to the 6–2 strategy, but the 6–2 strategy has a completely insignificant information ratio relative to the 12–7 strategy. The 12–7 strategy generates 0.84% per month relative to the 6–2 strategy, with a test statistic of 4.81. The 6–2 strategy generates only 0.07% per month relative to the 12–7 strategy, with a test statistic of 0.37.

Country indices, like industries and styles, exhibit some momentum at very short horizons. Last month's winning markets outperform last month's losing markets by 0.49% per month, with a test statistic of 2.91. The results of Table 10 are again robust, however, to including last month's returns in the short horizon strategy's past performance evaluation period. The strategy based on performance over the entire preceding six months generates 0.62% per month, with a test statistic of 3.02. The 6-1 strategy does not, however, contain significant information relative to the 12–7 strategy, while the 12–7 strategy has a large information ratio relative to the 6-1 strategy. The 6-1 strategy generates 0.22% per month relative to the 12–7 strategy with a test statistic of 1.23. The 12–7 strategy generates 0.78% per month relative to the 6-1 strategy with a test statistic of 4.48.

5.5. Commodity momentum

Commodities markets also exhibit significant momentum (Gorton, Hayahi, and Rouwenhorst, 2007), where trend following strategies are popular with practitioners. Commodities momentum strategies, like country momentum strategies, have statistically significant, though small, loadings on UMD. These UMD loadings explain less than 5% of the variation in the commodities momentum strategies' returns, however, and commodities markets consequently provide another largely independent test of the results established in this paper.

I construct commodities momentum strategies using the dollar returns to 31 commodities (aluminum, Brent crude, live cattle, cocoa, coffee, copper, corn, cotton, crude oil, feeder cattle, gas oil, gold, heating oil, lean hogs, Kansas wheat, lead, lumber, natural gas, nickel, orange juice, platinum, rubber, silver, soy beans, soy meal, soy oil, sugar, tin, unleaded gasoline, wheat, and zinc) employed in Asness, Moskowitz, and Pedersen (2008). These data originally come from the Chicago Board of Trade, the Chicago Mercantile Exchange, Intercontinental Exchange, the London Metal Exchange, the New York Board of Trade, the New York Commodities Exchange, the New York Mercantile Exchange, and the Tokyo Commodities Exchange. Returns on seven commodities are available back to February 1966 and for all 31 commodities starting in February 1995.

Table 11 reports the average monthly returns to commodities momentum strategies

Table 11.
Commodities momentum strategy spanning tests.

This table shows the results of time series regressions employing the returns to commodities momentum strategies constructed using past performance over different horizons. $\text{MOM}_{n,m}^{\text{com}}$ is the returns to the winner-minus-loser portfolio (tertiles), where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers February 1966 through November 2008.

Independent variables	$\text{MOM}_{12,7}^{\text{com}}$ as dependent variable			$\text{MOM}_{6,2}^{\text{com}}$ as dependent variable		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	1.18	1.08	1.14	0.39	0.08	0.28
	[4.06]	[3.65]	[3.94]	[1.33]	[0.27]	[0.94]
UMD		0.12			0.37	
		[1.64]			[5.28]	
$\text{MOM}_{6,2}^{\text{com}}$			0.09			
			[2.16]			
$\text{MOM}_{12,7}^{\text{com}}$						0.10
						[2.16]
Adj. R^2		0.003	0.007		0.050	0.007

based on intermediate horizon and recent past performances, as well as results of time series regressions of these strategies' returns on UMD and each other. These results are consistent with those observed in all the markets previously considered. Specifications 1 and 4 show the average monthly returns to the 12–7 and 6–2 strategies, respectively. The 12–7 strategy generates 1.18% per month, three times the 0.39% per month that the 6–2 strategy yields.The two strategies' realized annual Sharpe ratios over the sample are 0.62 and 0.20, respectively. Specifications 2 and 5 show that both strategies have positive loadings on UMD, though the 12–7 strategy's loading is insignificant, while the 6–2 strategy's loading is more than three times as large and highly significant. That is, it appears that the correlation between commodities momentum strategies and conventional momentum strategies is driven largely by recent past performance. Specifications 3 and 6 show that the 12–7 strategy has a large, highly significant information ratio relative to the

6–2 strategy, but the 6–2 strategy has a completely insignificant information ratio relative to the 12–7 strategy. The 12–7 strategy generates 1.14% per month relative to the 6–2 strategy, with a test statistic of 3.94, while the 6–2 strategy generates 0.28% per month relative to the 12–7 strategy, with a test statistic of 0.94.

While there is no 6–2 momentum in commodities, commodities exhibit strong momentum at very short horizons, driving the popularity of trend following strategies. Last month's winning commodities outperform last month's losing commodities by 1.39% per month, with a test statistic of 4.47. In fact, performance in the previous month is so important that including it in the short horizon past performance evaluation period improves the strategy's performance so much that it has a significant information ratio relative to the intermediate horizon momentum strategy. The 6-1 strategy generates 0.89% per month relative to the 12–7 strategy, with a test statistic of 2.91. The 6-1 strategy performs worse, however, than the strategy based on last month's performance alone. Including past performance in months two to six prior in the selection criteria actually reduces the profitability of the very short horizon industry momentum strategy. Including the most recent month in recent past performance also fails to help explain the performance of the strategy based on intermediate horizon past performance. The 12–7 strategy generates 1.04% per month relative to the 6-1 strategy, with a test statistic of 3.57.

The strategies based on intermediate past performance ($\mathrm{MOM}^{\mathrm{com}}_{12,7}$) and last month's performance ($\mathrm{MOM}^{\mathrm{com}}_{1,0}$) have similar Sharpe ratios. The strategy based on recent past performance ($\mathrm{MOM}^{\mathrm{com}}_{6,2}$) yields statistically insignificant returns. The three strategies are almost orthogonal. Consequently the ex post mean-variance efficient portfolio of the three strategies is essentially a 50-50 mix of the 12–7 and 1-0 strategies.

5.6. Currency momentum

Currencies also exhibit momentum but, unlike the other strategies I have considered thus far, currency momentum strategies do not load significantly on UMD. Because these strategies' returns are essentially uncorrelated with the returns to conventional momentum strategies constructed in the cross section of US equities, they represent perhaps the best independent test of the results presented in this paper.

I construct currency momentum strategies using the dollar returns to 19 foreign currencies (the British pound, the Italian lira, the Belgian franc, the French franc, the Swiss franc, the German mark, the Dutch guilder, the Japanese yen, the Hong Kong dollar, the South African rand, the Canadian dollar, the Singapore dollar, the Malaysian ringgit, the Australian dollar, the New Zealand dollar, Swedish krona, the Norwegian krone, the Danish krone and the euro) employed in Lustig, Roussanov and Verdelhan (2008). Strategies are constructed using futures contracts. The strategy that buys a forward contract that delivers a foreign currency and bonds that mature on the delivery date with a face value of the futures price costs $B_t(T)F_t(T)$, where $B_t(T)$ is the time-t price of a bond that matures T in the future and $F_t(T)$ is the time-t forward price of the currency for delivery T in the future. The strategy pays off the spot price of the foreign currency on the delivery date. The net return to the strategy is consequently $S_{t+T}/\left(B_t(T)F_t(T)\right) - 1$. Covered interest parity implies $F_t(T) = \tilde{B}_t(T)S_t/B_t(T)$, where $\tilde{B}_t$ is the time-t foreign currency cost of the foreign bond that matures T in the future, so the strategy's return can also be expressed as $S_{t+T}/\left(\tilde{B}_t(T)S_t\right) - 1$, the return to buying foreign currency and lending it out risk-free. Monthly returns are calculated using daily quotes in both the spot and futures markets, obtained from DataSteam and Barclays. Data are available for 9 currencies back to November 1983, peaks at 18 currencies in 1985, and falls to 13 with the introduction of the Euro in 1999. The data run through August 2007. Eliminating the least liquid currencies

Table 12. Currency momentum strategy spanning tests

This table shows the results of time series regressions employing the returns to currency momentum strategies constructed using past performance over different horizons. $\text{MOM}^{\text{cur}}_{n,m}$ is the returns to the winner-minus-loser portfolio (tertiles), where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers November 1984 through August 2007.

Independent variable	$y = \text{MOM}^{\text{cur}}_{12,7}$					$y = \text{MOM}^{\text{cur}}_{6,2}$				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Intercept	0.57	0.52	0.40	0.48	0.39	0.36	0.36	0.06	0.19	-0.04
	[4.15]	[3.76]	[2.73]	[3.58]	[2.71]	[2.43]	[2.34]	[0.41]	[1.30]	[-0.24]
UMD		0.06					0.01			
		[1.93]					[0.25]			
CARRY			0.18		0.11			0.32		0.28
			[2.98]		[1.77]			[4.98]		[4.32]
$\text{MOM}^{\text{cur}}_{6,2}$				0.25	0.22					
				[4.70]	[4.00]					
$\text{MOM}^{\text{cur}}_{12,7}$									0.30	0.25
									[4.70]	[4.00]
Adj. R^2		0.010	0.028	0.072	0.079		0.0	0.080	0.072	0.128

from the sample leaves the results qualitatively unchanged.

Table 12 reports results from tests that employ currency momentum strategies. The table reports average monthly returns to strategies based on intermediate horizon and recent past performances, as well as time series regressions of these strategies' returns on the returns to explanatory strategies. These explanatory strategies consist of UMD, the strategies themselves, and a factor based on returns to the carry trade, which Lustig, Roussanov, and Verdelhan (2008) report explains a significant portion of the returns to short horizon currency momentum. This carry factor (CARRY) is constructed by selling funding currencies (those from the 30% of countries with the lowest interest rates) and buying target currencies (those from the 30% of countries with the highest interest rates). The factor generates an average of 0.93% per month, and these returns are highly significant (test statistic equal to 6.92).

The table reports results that are again consistent with those observed in the cross section of US equities, industries, investment styles, international markets, and commodities. Specifications 1 and 6 show the average monthly returns to the 12–7 and 6–2 strategies. The 12–7 strategy generates 0.57% per month, while the 6–2 strategy yields 0.36% per month .The two strategies' realized annual Sharpe ratios over the sample are 0.84 and 0.35, respectively. Specifications 2 and 7 show that neither strategy loads significantly on UMD. Specifications 3 through 5 demonstrate that the carry strategy and the 6–2 strategy cannot explain the returns to the 12–7 strategy, either individually or jointly, while specifications 8 through 10 show that the returns of the 6–2 strategy are insignificant relative to the carry strategy and the 12–7 strategy, both individually and jointly.

Currency markets, like international markets, industries, and styles, exhibit momentum at very short horizons. Last month's winning currencies outperform losing currencies by 0.48% per month, with a test statistic of 3.21. The results of Table 12 are robust, however, to including last month's returns in the short horizon past performance evaluation period. The strategy based on performance over the entire preceding six months generates 0.47% per month, with a test statistic of 3.02. The 6-1 strategy does not, however, contain significant information relative to the 12–7 strategy. The 12–7 strategy has a large information ratio relative to the 6-1 strategy. The 6-1 strategy generates 0.29% per month relative to the 12–7 strategy with a test statistic of 1.86. The 12–7 strategy generates 0.45% per month relative to the 6-1 strategy with a test statistic of 3.38.

6. Relation to other known results

This section places my main results—that intermediate horizon, not recent, past performance primarily drives momentum—in the context of the literature. It also demonstrates the robustness of the results. In particular, this section shows that the results hold after controlling for the 12-month effect noted by Jegadeesh (1990) and studied in detail by Heston and Sadka (2008); the results are robust to controlling for post earnings announcement drift, which explains short horizon momentum but not intermediate horizon momentum; intermediate horizon momentum cannot be explained by disposition effects or capital gains overhang, though capital gains overhang does explain the poor January performance of intermediate horizon momentum strategies, as it does the poor January performance of momentum strategies more generally; and the results are essentially unrelated to the consistency of performance result of Grinblatt and Moskowitz (2004).

6.1. 12-month effect

For US equities, performance 12 months prior to portfolio formation is particularly important for predicting expected returns (Jegadeesh, 1990, and Heston and Sadka, 2008), especially for small stocks. While this 12-month effect contributes to the profitability of momentum strategies, it cannot explain the difference in the performance of strategies based on intermediate horizon and recent past performance constructed within the cross section of US equities. Section 5 provides indirect evidence of this, because momentum strategies based on intermediate horizon past performance perform much better than strategies based on recent past performance even in markets that do not exhibit the 12-month effect observed in US equities (e.g., international indices, commodities markets and currency markets). This section provides direct evidence that momentum strategies based on intermediate horizon past performance outperform those based on recent past performance independent of the 12-month effect.

Table 13 presents the results of spanning tests employing $\text{MOM}_{12,12}$, $\text{MOM}_{11,7}$, and $\text{MOM}_{6,2}$. The table shows that both $\text{MOM}_{12,12}$ and $\text{MOM}_{11,7}$ contain significant independent information regarding future returns, while $\text{MOM}_{6,2}$ does not. The first three

Table 13.
Spanning tests of the 12-month effect.

Time series regressions employing the returns to momentum strategies constructed using past performance over different horizons. $\text{MOM}_{n,m}$ is the returns, hedged for size and industry-adjusted booked-to-market, of the winner-minus-loser (decile) strategy, where winners and losers are based on cumulative returns from n to m months (inclusive) prior to portfolio formation. The sample period covers January 1927 through December 2008.

Independent	$y = \text{MOM}_{12,12}$			$y = \text{MOM}_{11,7}$			$y = \text{MOM}_{6,2}$		
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.59	0.68	0.56	0.78	0.73	0.60	0.55	0.32	0.22
	[3.63]	[4.16]	[3.46]	[3.94]	[3.96]	[3.26]	[2.43]	[1.52]	[1.03]
$\text{MOM}_{12,12}$				0.31		0.21	0.30		0.17
				[8.15]		[5.84]	[6.96]		[4.09]
$\text{MOM}_{11,7}$	0.21		0.16					0.46	0.42
	[8.15]		[5.84]					[13.9]	[12.6]
$\text{MOM}_{6,2}$		0.16	0.10		0.36	0.33			
		[6.96]	[4.09]		[13.9]	[12.6]			
Adj. R^2	0.062	0.046	0.077	0.062	0.164	0.191	0.046	0.164	0.177

specifications show that $\text{MOM}_{12,12}$ has a large information ratio relative to both $\text{MOM}_{11,7}$ and $\text{MOM}_{6,2}$, either individually or jointly. The middle three specifications show that $\text{MOM}_{11,7}$ has a large information ratio relative to both $\text{MOM}_{12,12}$ and $\text{MOM}_{6,2}$, either individually or jointly. Month 12 prior cannot explain the profitability of intermediate horizon momentum strategies. The last three specifications show that the 12-month effect does not help explain the profitability of short horizon momentum strategies. $\text{MOM}_{6,2}$ has significant information relative to $\text{MOM}_{12,12}$, but not relative to $\text{MOM}_{11,7}$.

Double sorting stocks on $r_{12,12}$ and $r_{11,7}$ also produces large, significant return spreads in both directions, consistent with the results presented in Table 13.

6.2. Earnings momentum

Chan, Jegadeesh, and Lakonishok (1996) find that earnings surprises and past performance each predict large drifts in future returns after controlling for each other. This section shows that the predictive power of recent past performance largely disappears after controlling for earnings surprises, but that earnings surprises cannot explain the predictive power of intermediate horizon past performance.

Table 14 reports the results of Fama-MacBeth regressions employing past performance measures and standardized unexpected earnings surprises (SUE, the deviation of the last quarterly earnings from its average over the preceding four quarters, scaled by one quarter lagged assets), and controls for prior month's performance, size, and book-to-market. The first two specifications show that including standardized unexpected earnings reduces the power of prior year's performance ($r_{12,2}$), but that the past performance variable retains significant explanatory power. Specifications 3 and 4 show that including SUE only marginally reduces the explanatory power of intermediate horizon past performance, while specifications 5 and 6 show that SUE largely subsumes recent past performance. Specification 7 shows that my primary result—that intermediate past performance has more power than recent past performance predicting returns—holds over the sample period. Specification 8 shows that controlling for standardized unexpected earnings strengthens this result.

These Fama-MacBeth regressions suggest that controlling for SUE reduces the importance of recent past performance. Tests employing portfolio sorts yield similar results. Controlling for SUE when constructing momentum strategies based on recent past performance reduces the strategies' profitabilities. For example, a quintile winner-minus-loser strategy based on recent past performance generated 0.48% per month over the SUE sample, significant at the 5% level. Similar strategies constructed within SUE deciles return on average only 0.35% per month, and a GRS test fails to reject the hypothesis that the ten strategies' true expected returns over the sample are jointly zero.

Table 14. The role of earnings momentum

This table reports results of Fama-MacBeth regressions of firms' returns on past performance variables ($r_{12,2}$, $r_{12,7}$, and $r_{6,2}$) and standardized unexpected earnings (SUE, the deviation of a firm's most recent quarterly earnings from its average earnings over the previous four quarters, scaled by its assets lagged one quarter). Regressions include controls for prior month's returns, size, and book-to-market ($r_{1,0}$, log(ME), and log(BM), respectively). Independent variables are winsorized at the 1% and 99% levels. The sample period covers November 1972 through December 2008, and is determined be the availability of the quarterly earnings data used to construct SUE.

Independent variables	Slope coefficient ($\times 10^2$) and [test statistic] from Fama-MacBeth regressions under alternative specifications							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$r_{12,2}$	0.71	0.54						
	[4.89]	[3.76]						
$r_{12,7}$			0.93	0.84			0.93	0.84
			[6.16]	[5.38]			[6.37]	[5.52]
$r_{6,2}$					0.43	0.12	0.40	0.07
					[1.90]	[0.50]	[1.81]	[0.31]
SUE		32.3		32.7		33.6		33.1
		[18.4]		[18.2]		[17.9]		[18.0]
$r_{1,0}$	-5.34	-6.29	-5.35	-6.31	-5.35	-6.33	-5.41	-6.40
	[-12.5]	[-14.1]	[-12.3]	[-13.9]	[-12.4]	[-13.9]	[-12.8]	[-14.3]
ln(ME)	-0.12	-0.14	-0.11	-0.13	-0.09	-0.11	-0.12	-0.13
	[-2.72]	[-2.86]	[-2.35]	[-2.67]	[-2.06]	[-2.29]	[-2.73]	[-2.85]
ln(BM)	0.28	0.24	0.29	0.25	0.29	0.25	0.28	0.25
	[4.93]	[3.86]	[5.10]	[4.00]	[5.06]	[4.04]	[5.23]	[4.25]
$r_{12,7} - r_{6,2}$							0.52	0.76
							[2.64]	[3.43]

6.3. Disposition effects and capital gains overhang

Grinblatt and Han (2005) argue that disposition effects (i.e., the tendency of some investors to sell winning stocks and hold losing stocks) yield predictability in stock returns and that this predictability explains the profitability of momentum strategies. A reluctance to sell losers also results in losing stocks with large unrealized capital losses. Grinblatt and Moskowitz (2004) find that tax-loss selling drives strongly negative December returns for losing firms and that this explains a good portion of the profitability of momentum strategies. This subsection shows that disposition effects, and the associated trading related to capital gains overhang, cannot explain the difference in profitability between momentum strategies based on intermediate horizon past performance and recent past performance.

Frazzini (2006) considers the role that capital gains (or losses) experienced by holders of a stock play, through the disposition effect, in the speed that new information about that stock is impounded into prices. He consequently constructs a measure of the capital gains overhang for each stock. This measure is defined as the percentage deviation of the aggregate cost basis from the current price, where the aggregate cost basis is the holding weighted average purchase price of the stock by mutual funds in the Thompson Financial CDA/Spectrum Mutual Funds database. This measure is at least somewhat positively correlated, mechanically, with past returns. While Frazzini (2006) focuses on the interaction of his measure of capital gains overhang and post-announcement price drift, the measure itself can be used to predict returns.

The gains-minus-losses (GML) strategy consists of buying high gain stocks (top quintile) and selling high loss stocks (bottom quintile). I consider only the equal-weighted strategy, as the effect is concentrated in small stocks. Equal-weighted GML generates 0.86% per month, with a test statistic of 3.44, over the Frazzini (2006) sample period from April 1980 through August 2002.

Disposition effects associated with unrealized gains and losses do not explain the performance of the 12–7 strategy and cannot, contrary to the results of Grinblatt and Han (2005), even explain the performance of the 12–2 strategy. Table 15 shows results of spanning tests on the capital gains overhang strategy, GML, and the three equal-weighted momentum strategies, $\text{MOM}^{\text{ew}}_{12,2}$, $\text{MOM}^{\text{ew}}_{12,7}$, and $\text{MOM}^{\text{ew}}_{6,2}$. The first four specifications demonstrate that both the 12–2 and 12–7 strategies price GML, while the converse are false. The last two specifications show that GML prices the 6–2 strategy, while the

Table 15.
Spanning tests employing momentum and capital gains overhang strategies.

This table reports results of time series regressions using the equal-weighted returns to momentum strategies based on past performance at different horizons ($\mathrm{MOM}_{n,m}^{ew}$), and the equal-weighted returns to the capital gains-minus-losses strategy (GML). The sample period covers April 1980 through August 2002, employed in Frazzini (2006).

Dependent variable	GML	$\mathrm{MOM}_{12,2}^{ew}$	GML	$\mathrm{MOM}_{12,7}^{ew}$	GML	$\mathrm{MOM}_{6,2}^{ew}$
Independent variable	$\mathrm{MOM}_{12,2}^{ew}$	GML	$\mathrm{MOM}_{12,7}^{ew}$	GML	$\mathrm{MOM}_{6,2}^{ew}$	GML
Intercept	-0.15	0.46	-0.05	0.58	0.46	0.02
	[-1.27]	[3.21]	[-0.26]	[3.66]	[2.45]	[0.12]
Slope	0.74	1.06	0.81	0.64	0.75	0.60
	[31.2]	[31.2]	[16.7]	[16.7]	[14.7]	[14.7]
Adj. R^2	0.783	0.783	0.510	0.510	0.444	0.444

converse is false. It appears that the 12–7 and 12–2 strategies contains all of the pertinent pricing information in the GML strategy, which in turn contains all of the pertinent pricing information in the 6–2 strategy. But capital gains overhang does not explain either conventional momentum or momentum constructed on the basis of intermediate horizon past performance.

While a trading strategy based on a univariate sort on capital gains overhang fails to explain momentum, controlling for capital gains overhang when constructing momentum strategies both improves momentum strategies' performance and provides compelling evidence for the tax effects story for standard momentum strategies' poor January performance. Further analysis of these results are provided in the appendix.

6.4. *Consistency of performance*

Grinblatt and Moskowitz (2004) argue that high past returns achieved with a series of steady positive months generate larger expected returns than the same level of past returns achieved through a few extraordinary months. They find that consistent winners, defined as stocks that had positive returns in at least eight of the 11 months from

$t-12$ to $t-2$ (inclusive), significantly outperform other stocks, even after controlling for the level of past performance. In particular, they find a significant coefficient on a consistent winners indicator in Fama-MacBeth regressions that include past performance as an explanatory variable (though portfolios of consistent winners fail to significantly outperform portfolios of stocks with similar prior performance achieved less consistently). Watkins (2003) also finds that firms that had positive (negative) returns every month for six straight months significantly outperform (underperform) the market over the following six months, though this outperformance (underperformance) disappears after controlling for momentum (UMD).

These results could be driven by the importance of intermediate horizon past performance. Consistent winners are unlikely to have performed poorly over the crucial period spanning the first half of the previous year. A consistent winner, as defined by Grinblatt and Moskowitz (2004), is guaranteed to have had at least two winning months over this period and is likely to have had at least four winning months over that time. It is therefore reasonable to ask if the power of the consistent winners indicator derives from its ability to help distinguish stocks that performed well at intermediate horizons from stocks that have performed equally well over the past year due to exceptional recent performance.

A series of Fama-MacBeth regressions tests whether the fact that intermediate horizon past performance, and not recent past performance, has power predicting returns is related to the consistency of performance result. These tests regress stocks' returns on past performance, measured at different horizons, and an indicator as to whether the stocks were consistent winners, I^{CW}. Following Grinblatt and Moskowitz (2004), this variable takes the value one, for each stock and in each month, if the stock had positive returns in eight of the first 11 months of the preceding year and zero otherwise.

This consistent winner indicator conflates two effects. Stocks that have won in eight out of 11 months tend to be both big winners and consistent performers, i.e., stocks in the upper tail of the past performance distribution, and also stocks that have realized low return volatility over the same period. In an attempt to disentangle these effects, some specifications include both a big winners indicator and realized volatility as explanatory variables. The big winners indicator, I^{BW}, takes the value one, for each stock and in each month, if the stock was in the top quintile of performers over the first 11 months of the previous year and zero otherwise. Realized volatility, $\sigma_{12,2}$, is the annualized standard deviation of monthly returns over the same period. The slope coefficients from a Fama-MacBeth regression of the consistent winners indicator, I^{CW}, onto the big winners indicator and realized volatility, I^{BW} and $\sigma_{12,2}$, are 0.28 and -0.35 respectively, with test statistics of 66.2 and -30.0. The time series average of the cross sectional variation in I^{CW} explained by I^{BW} and $\sigma_{12,2}$ is 15.3%.

Table 16 reports results of these regressions, which include controls for prior month's performance, size, and book-to-market. The table suggests that the consistency of performance result of Grinblatt and Moskowitz (2004) is essentially unrelated to the disparity in power between intermediate horizon and recent past performance for predicting returns.

Specification 1 shows the consistency of performance result of Grinblatt and Moskowitz (2004). This specification shows that the consistent winners indicator has significant power predicting expected returns, even after controlling for past performance. It gives no indication, however, that the consistency of performance result is related to the results presented in this paper. After controlling for consistent winners, the coefficient on intermediate horizon past performance is still significantly higher that that on recent past performance, consistent with the results presented in Table 1.

Specifications 2 and 3 include the big winners indicator and realized volatility as explanatory variables, respectively, and find a significant role for each. Big winners generate significantly higher expected returns, even after controlling for the level of past

Table 16.
Testing the role of consistency of performance.

This table reports results of Fama-MacBeth regressions of firms' returns on intermediate and recent past performance ($r_{12,7}$ and $r_{6,2}$, respectively) and variables related to consistency of performance. The consistent winners indicator, I^{CW}, takes the value one if a stock had positive returns in eight of the first 11 months of the preceding year and zero otherwise. The big winners indicator, I^{BW}, takes the value one if a stock was in the upper quintile of past performance in the first 11 months of the preceding year and zero otherwise. Realized volatility, $\sigma_{12,2}$, is the annualized standard deviation of monthly returns over the first 11 months of the preceding year. Independent variables are winsorized at the 1% and 99% levels. The sample period covers January 1927 through December 2008. The early sample covers January 1927 through December 1967, while the late sample covers January 1968 through December 2008,

	Slope coefficient ($\times 10^2$) and [test statistics] under alternative specifications					
					Subsample	
independent variables	(1)	(2)	(3)	(4)	Early	Late
$r_{12,7}$	1.21	1.02	1.21	1.15	1.40	0.91
	[7.42]	[4.94]	[6.90]	[6.66]	[4.66]	[5.24]
$r_{6,2}$	0.70	0.48	0.72	0.69	0.82	0.55
	[2.91]	[1.73]	[2.93]	[2.86]	[2.02]	[2.15]
I^{CW}	0.30			0.15	0.12	0.19
	[2.81]			[1.46]	[0.58]	[2.86]
I^{BW}		0.18		0.18	0.03	0.33
		[2.96]		[3.44]	[0.37]	[4.67]
$\sigma_{12,2}$			-0.84	-0.89	-0.41	-1.37
			[-3.10]	[-3.28]	[-0.89]	[-4.65]
$r_{1,0}$	-7.69	-7.82	-7.97	-7.90	-9.44	-6.37
	[-20.5]	[-20.7]	[-21.6]	[-21.7]	[-16.2]	[-14.8]
ln(ME)	-0.13	-0.13	-0.17	-0.17	-0.17	-0.17
	[-4.01]	[-3.82]	[-5.70]	[-5.79]	[-3.69]	[-4.61]
ln(BM)	0.25	0.28	0.23	0.22	0.18	0.26
	[5.45]	[5.77]	[5.48]	[5.38]	[2.74]	[5.33]
$r_{12,7} - r_{6,2}$	0.52	0.54	0.49	0.47	0.58	0.36
	[2.19]	[2.28]	[2.54]	[2.41]	[1.67]	[2.02]

performance, suggesting a nonlinearity in the relation between past performance and expected returns. Higher realized volatility is also associated, even after controlling for past performance, with lower expected returns. That is, this specification finds a significant role for consistency of performance, as measured by realized volatility. In both cases the coefficient on intermediate horizon past performance is significantly higher than that on recent past performance.

Specification 4 suggests that the significance of the consistent winners variable derives, at least in part, from its correlation with the big winners indicator and realized volatility. Including the big winners indicator and realized volatility as regressors cuts the slope coefficient on the consistent winners indicator in half, to the point that it is no longer significant, while leaving the slope coefficients on the big winners indicator and realized volatility, and their significances, essentially unchanged. That is, the consistent winners variable has power predicting returns because consistent winners tend to be big winners with low realized recent volatility, and not because they are consistent winners, per se. In this specification the coefficient on intermediate horizon past performance again significantly exceeds that on recent past performance.

The last two specifications repeat the test of Specification 4, which employs all three variables related to consistency of performance, in the early and late subsamples of the data. They show that whatever power the consistency variables have for predicting returns is concentrated completely in the second half of the sample, covering January 1968 to December 2008. None of the consistency variables is significant in the first half of the data.

7. Conclusion

Momentum does not accurately describe the returns to buying winners and selling losers. On average recent winners that were intermediate horizon losers significantly under-perform recent losers that were intermediate horizon winners. This fact is inconsistent with the traditional view of momentum, that rising stocks tend to keep rising, while falling stocks tend to keep falling. Intermediate horizon past performance, not recent past performance, primarily drives momentum not just in the cross section of US equities, but also in industries, investment styles, international equity indices, commodities, and currencies.

These findings pose significant difficulties for models that purport to explain momentum. Popular behavioral explanations predicated on biases in the way that investors interpret information generate positive short-lag autocorrelations in prices. According to these explanations, security prices underreact to news, which is incorporated slowly into prices, yielding price momentum. Popular rational explanations predicated on positive correlations between past performance and risk exposure generate similar predictions of short-lag autocorrelations in prices.

Such short-lag autocorrelations are inconsistent with the data. Instead, the observed term structure of momentum information exhibits significant information in past performance at horizons of 12 to seven months; recent returns that are largely irrelevant after controlling for performance at intermediate horizons, at least over the last four decades; and an abrupt drop-off at 12 months, beyond which there is no return predictability after controlling for the Fama-French factors. Explanations consistent with the observed term structure of momentum are not readily apparent and provide a significant challenge for future research.

Understanding that intermediate horizon past performance primarily drives momentum also facilitates the design of more profitable trading strategies. Including information regarding largely irrelevant recent past performance in the portfolio selection criteria reduces strategy performance. Ignoring recent performance when selecting stocks significantly improves momentum strategy Sharpe ratios. Performance is particularly enhanced in liquid, large cap stocks, which exhibit more momentum than is commonly recognized.

A. Appendix: Disposition effect and seasonality

Controlling for capital gains overhang when constructing momentum strategies both improves momentum strategies' performance and provides compelling evidence for the tax effects story for standard momentum strategies' poor January performance.

Table 17 presents results obtained by double sorting on past returns and capital gains overhang. Caution must be taken because the two sorts are correlated, yielding relatively thin high-low and low-high corners (in particular, the losers with large capital gains overhang portfolio averages only 27 firms).

Even so, Table 17 argues strongly that the capital gain overhang's power to predict returns in univariate sorts derives completely from its correlation with past returns. The left half of the table shows that the capital gains overhang has no power predicating returns after controlling for differences in past returns. A GRS test fails to reject the hypothesis that the true expected returns to the five GML strategies constructed within past performance quintiles are jointly zero ($F_{5,253} = 0.605$ for a p-value of 69.6%). Because these portfolios load significantly on UMD, however, these strategies generally generate significantly negative four-factor alphas, and a GRS test rejects the hypothesis that the true four factor alphas are jointly zero ($F_{5,249} = 2.338$ for a p-value of 4.2%).

Controlling for capital gains overhang does, however, improve momentum's performance. This result is similar in spirit to the main finding of Frazzini (2006), which finds that controlling for capital gains overhang improves the performance of earnings momentum strategies. The right half of Table 17 shows that within capital gains quintiles the equal-weighted 12–2 momentum strategies generate 1.44 to 1.94% per month, with test statistics ranging from 5.99 to 6.72. These compare favorably with the unconditional equal-weighted 12–2 strategy, which generates 1.37% per month, with a test statistic of

Table 17.
Spreads and factor loadings from double sorts on $r_{12,2}$ and capital gains overhang.

Time series regressions using the returns to momentum strategies constructed within capital gains quintiles, and the returns to the capital gains-minus-losses strategy constructed within past performance quintiles. GML denotes the equal-weighted gains-minus-losses portfolio (quintiles). $\text{MOM}^{\text{ew}}_{12,2}$ denotes the equal-weighted winner-minus-loser portfolio (quintiles), based on cumulative returns from 12 to two months (inclusive) prior to portfolio formation. The sample period covers April 1980 to August 2002, employed in Frazzini (2006).

	GML conditioned on $r_{12,2}$					$\text{MOM}^{\text{ew}}_{12,2}$ conditioned on capital gains				
	Past performance ($r_{12,2}$) quintile					Capital gain overhang quintile				
	(L)	(2)	(3)	(4)	(W)	(L)	(2)	(3)	(4)	(H)
Panel A: average monthly returns										
$E[r^e]$	-0.18	-0.16	-0.16	-0.32	0.02	1.74	1.44	1.47	1.78	1.94
	[-0.65]	[-0.81]	[-0.77]	[-1.18]	[0.05]	[6.72]	[6.13]	[6.97]	[6.24]	[5.99]
Panel B: Fama-French four factor loadings										
α	-0.59	-0.40	-0.36	-0.77	-0.39	1.05	0.83	0.93	1.22	1.25
	[-2.05]	[-2.08]	[-1.92]	[-3.02]	[-1.47]	[5.16]	[5.07]	[5.42]	[4.84]	[4.50]
MKT	-0.07	-0.08	-0.10	-0.09	-0.07	0.03	0.07	0.03	0.06	0.04
	[-1.03]	[-1.65]	[-2.22]	[-1.45]	[-1.04]	[0.64]	[1.61]	[0.60]	[0.93]	[0.55]
SMB	0.05	-0.09	-0.35	-0.30	-0.30	0.14	0.07	-0.01	-0.22	-0.21
	[0.53]	[-1.59]	[-6.14]	[-3.87]	[-3.70]	[2.28]	[1.33]	[-0.19]	[-2.83]	[-2.41]
HML	0.21	0.01	0.00	0.33	0.04	0.04	-0.12	0.01	-0.15	-0.13
	[1.94]	[0.08]	[0.01]	[3.49]	[0.37]	[0.57]	[-2.01]	[0.07]	[-1.57]	[-1.24]
UMD	0.35	0.30	0.28	0.35	0.44	0.67	0.65	0.54	0.63	0.76
	[5.39]	[6.70]	[6.44]	[6.01]	[7.33]	[14.5]	[17.5]	[13.9]	[11.0]	[12.0]

4.57, over the Frazzini (2006) sample period April 1980 through August 2002.

Fig. 6, which plots the average returns to the ten long/short strategies shown in Table 17 by calendar month, provides compelling evidence for the tax effects story for momentum's poor January performance. The gains-minus-losses portfolios, after controlling for past returns, are distinguished only by their terrible January performance (left). The momentum portfolios generally have positive average returns even in January after controlling for capital gains overhang.

Because capital gains overhang drives momentum's poor January performance, the

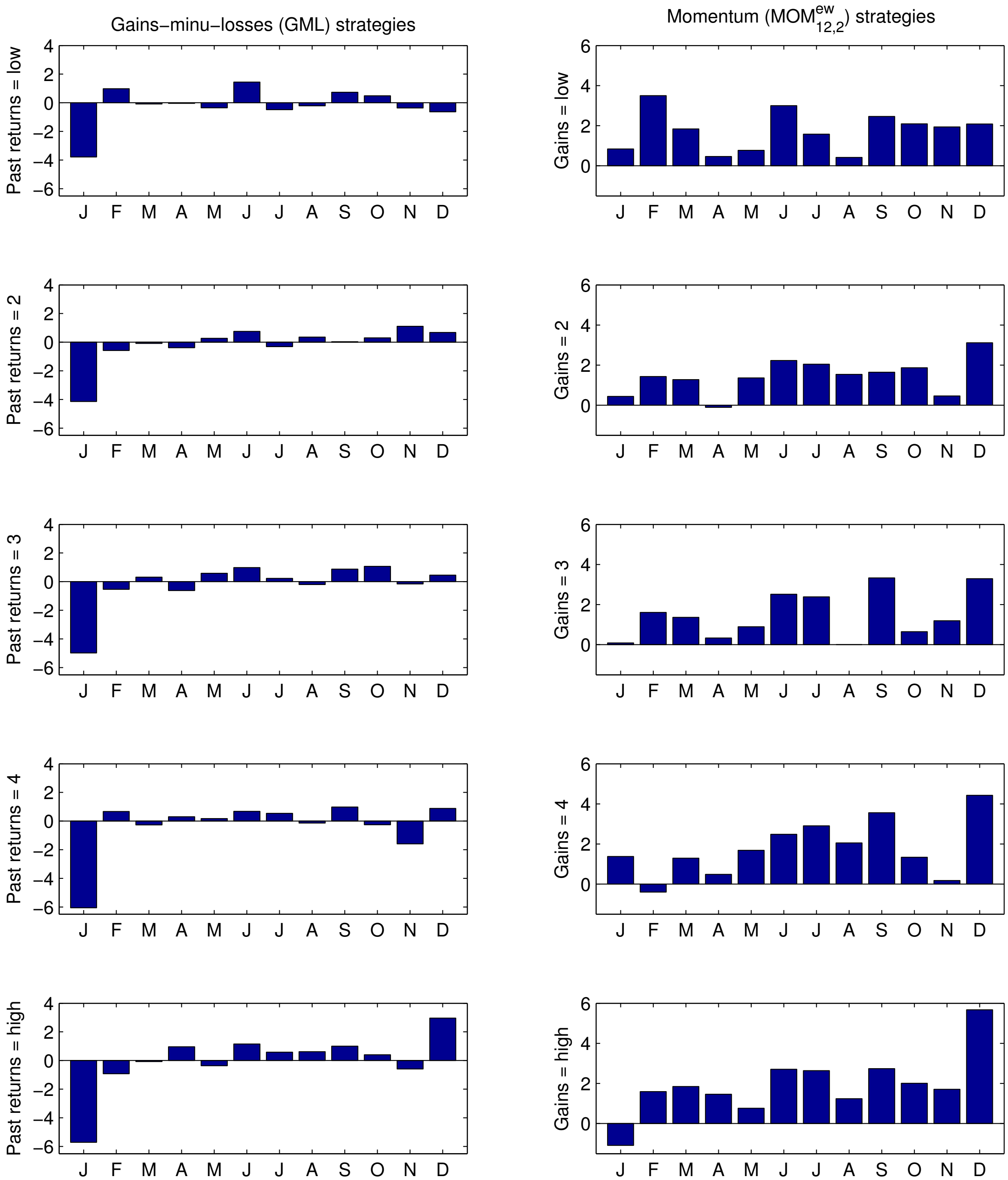

Fig. 6. Conditional average returns to gains-minus-losses (GML) and momentum (MOM$^{ew}_{12,2}$) strategies, by calendar month. This figures show the average monthly returns (in percent), by calendar month, to capital gain/loss strategies constructed within past return quintiles (left) and momentum strategies constructed within capital gain overhang quintiles (right). The sample period covers April 1980 to August 2002, employed in Frazzini (2006).

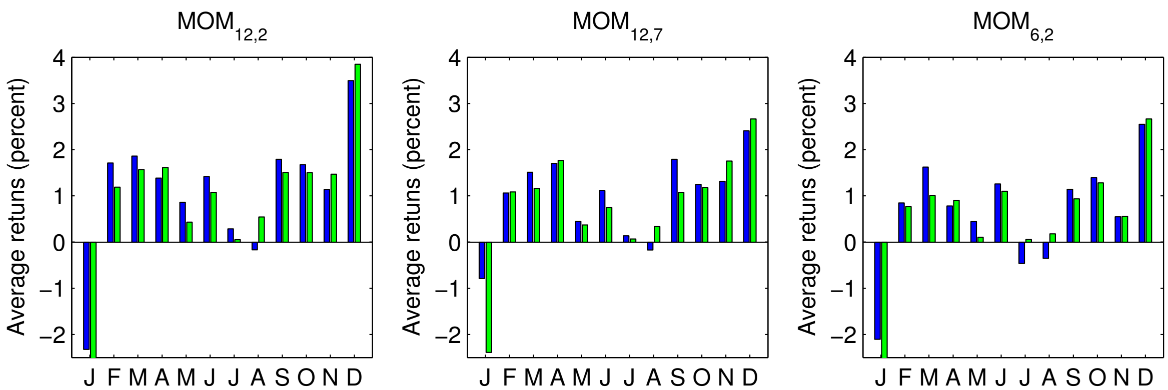

Figure 7. Returns to momentum strategies, by calendar month. The figures show the average returns, by calendar month, to the three momentum strategies $\text{MOM}_{12,2}$, $\text{MOM}_{12,7}$, and $\text{MOM}_{6,2}$. Value-weighted returns are shown in black. Equal-weighted returns are shown in grey. The January returns to $\text{MOM}^{\text{ew}}_{12,2}$ and $\text{MOM}^{\text{ew}}_{6,2}$ are -3.84% and -3.88%, respectively.

expectation is that the 12–7 strategies outperform the 12–2 and 6–2 strategies in January. Returns from prior months 12 through seven are mechanically less correlated with past one year returns, and consequently with unrealized capital gains and losses, than are returns from prior months 12 through two. Returns from prior months 12 through seven are slightly more correlated with past one year returns than are returns from prior months six through two. These returns from farther back are less correlated with the aggregate capital gains overhang, however, because more of the gains or losses associated with returns in the more distant past have been realized in the course of six months of normal trading. It is thus reasonable to ask how much of the 12–7 strategy's outperformance of the 12–2 and 6–2 strategies is due to differences in their average January returns.

Fig. 7, which depicts average returns to the 12–2, 12–7 and 6–2 strategies by calendar month, confirms these predictions. The average January returns to the 12–7 strategies, -0.85% and -2.12% value and equal-weighted, respectively, exceed those to the 12–2 strategies (-2.15% and -3.84%) and the 6–2 strategies (-1.73% and -3.88%). These relatively modest differences in average January returns are insufficient, however, to explain the superior performance of the 12–7 strategies.

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