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The Profitability of Momentum Investing

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1. INTRODUCTION

Among investment strategies designed to exploit stock mispricing, probably the simplest are those based only on historical returns. Evidence on the profitability of these strategies constitutes a rejection of the efficient markets hypothesis — a cornerstone of modern finance — at the most basic (weak-form) level. Not surprisingly, whether historical returns predict future abnormal returns has been of enduring academic interest going back almost forty years.

Investment strategies based on historical returns, examined in the literature, fall into two general types. Overreaction or contrarian strategies rank stocks on their investment performance over some previous period and recommend buying past losers and selling past winners. Momentum strategies make an equivalent ranking but recommend buying past winners and selling past losers. Both strategies normally maintain prior ranking periods and subsequent investment holding periods of similar length. What keeps contrarian and momentum strategies from being mutually inconsistent is that the former are based on long-term ranking periods, usually of three years of more, while

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the latter are based on medium-term ranking periods, usually between three and twelve months.[1]

There are several published studies of long-term contrarian strategies, for both the UK and the US. The earliest and most influential study is by DeBondt and Thaler (1985), who find that when US stocks are ranked on their returns over the past three to five years, stocks with the lowest past returns earn high returns over the subsequent three to five years, and vice versa. Subsequent studies of contrarian strategies have sought explanations for return reversals. These include: (i) failure to adjust properly for time-varying risk (Chan, 1988; and Ball and Kothari, 1989); (ii) manifestation of other effects such as the distressed firm effect (Chan and Chen, 1991) and the size effect (Zarowin, 1990); and (iii) market-microstructure related effects (Conrad and Kaul, 1993; and Ball, Kothari and Shanken, 1995). Results from UK studies of overreaction tend to be consistent with the US evidence of Debondt and Thaler (1985). Early studies (Power, Lonie and Lonie, 1991; and MacDonald and Power, 1991) find evidence of long-term overreaction for a limited data sample. Clare and Thomas (1995) find significant evidence of overreaction for two-year ranking and holding periods and weaker evidence for three-year ranking and holding periods for random samples of 1,000 UK stocks from 1955 to 1990. However, their further analysis suggests that the evidence of overreaction is attributable to the size effect. Finally, Dissanaike (1997), basing his study on the constituents of the *FT 500 Index* from 1962 to 1990 and using four-year ranking periods, finds evidence of significant overreaction for holding periods ranging from two to four years. Allowing for time-varying betas leaves these conclusions intact.

There are several published studies of momentum strategies using US data. The first paper to test the momentum strategy adopted in the current study is Jegadeesh and Titman (JT) (1993).[2,3] JT study the performance of NYSE and AMEX stocks over the period 1965 to 1989. They rank eligible stocks on their return performance over periods of 1, 2, 3, and 4 quarters, updated monthly. Corresponding to each ranking they form ten equally-weighted portfolios and measure the performance of these decile portfolios for holding periods varying from 1 to 4 quarters. JT find that the 6×6 momentum strategy[4] generates returns of about 1% per month, while their most profitable, 12×3

momentum strategy generates returns of as much as 1.49% per month.[5,6] More detailed analysis of the 6×6 strategy shows that trading profits cannot be explained by differences in systematic risk between past winners and losers, or by differences in the speed of price reaction to common factors. Instead, JT conclude that the evidence is consistent with profits being due to delayed price reaction to firm-specific information. JT also find that, with the exception of the first month, profits are positive in each of the 12 months after the six-month ranking period, but that over the following two years the strategy loses 50% of these initial gains.

Fama and French (1996) argue that the Fama and French (1993) three-factor model of expected returns can explain several of the documented anomalous patterns in average returns. The three factor model expresses the expected return on security i as:

$$E(R_i) = R_f + b_i[E(R_m) - R_f] + s_i E(SMB) + h_i E(HML), \qquad (1)$$

where $[E(R_m) - R_f]$ is the expected excess return on a broad market portfolio, $E(SMB)$ is the difference in returns between portfolios of small and large stocks (small minus big), and $E(HML)$ is the difference in returns between portfolios of high book-to-market and low book-to-market stocks (high minus low). Fama and French find, for example, that corresponding to contrarian strategies, long-term past losers have higher values of s_i and h_i than long-term past winners, indicating they behave like small distressed stocks. However, the three-factor model is unable to explain the continuation of medium-term returns for NYSE, AMEX, and Nasdaq stocks over the period 1963 to 1993.

To provide further insight into the underreaction exploited by momentum strategies, Chan, Jegadeesh, and Lakonishok (CJL) (1996) extend the analysis of Jegadeesh and Titman (1993) by examining earnings momentum strategies in addition to the JT price momentum strategies. The CJL price momentum strategy ranks stocks each month on their compound returns over the previous six months. The earnings momentum strategy also ranks stocks each month, but based on their most recent earnings surprises. CJL measure earnings surprise in three alternative ways. One is standardised unexpected earnings, popular in the post-earnings announcement drift literature. This is a stock's quarterly differenced earnings standardised by the standard deviation of quarterly differenced earnings over the previous eight quarters. The second is a stock's cumulative market-adjusted return over the four-day period starting two days before the most recent quarterly earnings announcement. The third is a measure of revisions in consensus analyst earnings forecasts over the previous six months (each revision scaled by opening stock price). Analysing earnings and price momentum strategies allows CJL to examine whether either strategy subsumes the other in terms of the information they exploit.

Considering NYSE, AMEX, and Nasdaq stocks over the period 1977 to 1993, CJL find that a 6×6 momentum strategy based on extreme deciles earns returns of 8.8% over the holding period. A corresponding earnings momentum strategy, based on analyst earnings forecast revisions, produces six month returns of 7.7%. CJL find that the price momentum effect is stronger and more persistent than the earnings momentum effect, while both effects are robust to the Fama–French three-factor model. Looking at the interaction between the two effects, CJL find that 41% of the six-month profits to the price momentum strategy occurs around the dates of subsequent earnings announcements. This leaves over half of the profits unrelated to quarterly earnings announcements. CJL conclude that prior return and earnings surprise each have marginal predictive power for future holding period returns.[7]

Subsequent empirical studies of momentum strategies have also tried to explain the sources of their apparent profits. Conrad and Kaul (1998) suggest that cross-sectional variation in mean returns can explain profits to momentum strategies on NYSE/AMEX stocks over the period 1948–1989.[8] Grundy and Martin (1998) find that a momentum strategy applied to NYSE/AMEX stocks over the period 1966–1995 earns Fama–French three-factor risk-adjusted returns of more than 1.3% per month. Neither cross-sectional variability in expected returns nor industry risk can explain these profits. Moreover, a momentum strategy that ranks stocks on their stock-specific return component outperforms one that ranks on total return. Moskowitz and Grinblatt (1999) argue that industry momentum strategies are more profitable than individual stock momentum strategies in the US and that after controlling for industry effects individual stock momentum strategies are for the most part insignificant.

Kraft (1999) examines the linkages between several trading strategies based on market underreactions to accounting and market data in the US. He finds that trading strategies based on fundamental financial statement ratios and unexpected earnings subsume other accounting-based and market-based trading strategies, including price momentum investment, and that this effect is concentrated in small firms.

As the momentum effect initially established itself as a robust phenomenon, at least in the US, behavioural theories based on investors who are not fully rational were developed to try and explain the effect. These theories attempt to explain the simultaneous effects of underreaction at medium-term horizons and overreaction at long-term horizons. Barberis, Shleifer and Vishny (BSV, 1998) develop a model motivated by the *representative heuristic* — whereby investors too readily label stocks based on recent data, ignoring the more complete statistical evidence on stock types — and *conservatism* — whereby investors are slow to update models in the face of new evidence. The former effect encourages overreaction, the latter underreaction. In their specific model, company earnings follow a random walk, but investors believe earnings are either mean-reverting (regime 1) or trending (regime 2). There is a regime-switching probability between regimes 1 and 2, but investors assume regime 1 is more likely. Overreaction occurs after a string of either positive or negative earnings shocks, which cements belief regime 2. For example, after a string of positive earnings shocks, although the next shock is equally likely to be positive or negative, there is less reaction to a positive shock, which is expected, than to a negative shock, which is not expected. The result is that the subsequent average return is negative. Underreaction occurs when belief regime 1 holds. Investors believe earnings shocks are more likely to be reversed, while in fact they are as likely to continue as to reverse. When a reversal occurs there is less price reaction than when a continuation occurs, and momentum is the outcome.

The behavioural model of Daniel, Hirshleifer, and Subrahmanyam (DHS, 1998) has two types of investors, informed and uninformed. Informed investors, who determine prices, are subject to two biases: they are overconfident and they attribute favourable outcomes to their own skill. Specifically, informed investors place greater confidence in private information and they tend to interpret public information that confirms their views as confirming their ability and public information that contradicts their views as noise. Thus, on average, news generates momentum in the medium-term, but the weight of public information eventually produces long-term reversals.

Finally, Hong and Stein (1999) develop a model with two types of agents: newswatchers and momentum traders. Newswatchers form strategies based on private information — which diffuses slowly to other newswatchers — and they ignore the information in current or past prices. Momentum traders do condition their trades on past prices, but their strategies are simple functions of past prices. 'Early' momentum traders themselves create momentum, encouraging 'late' momentum traders, eventually resulting in overreaction.

While these three behavioural theories each explain the simultaneous existence of medium-term underreaction and long-term overreaction, the phenomena they are designed to explain, Fama (1998) argues that they fail to explain the bigger picture.[9] For example, the BSV model fails to explain the long-term post-event abnormal returns of the same sign as long-term pre-event returns associated with dividend omissions and initiations, stock splits, proxy contests, and spinoffs. The DHS model predicts that so-called selective events — those such as stock repurchases that occur to take advantage of stock mispricing — are associated with price momentum. Fama points out that this prediction is inconsistent with evidence of post-announcement returns with the opposite sign to announcement returns associated with exchange listings, proxy fights, and IPOs (and with the zero followed by negative returns for acquiring firms in mergers).[10]

All of the previous evidence on momentum strategies is based on US data. Rouwenhorst (1998) examines an international momentum strategy using stocks from 12 European countries: Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, and the UK. The data covers the period 1980 to 1995. Using the methodology of Jegadeesh and Titman (1993), Rouwenhorst finds that return continuation is present in all countries, and an internationally diversified momentum strategy earns returns of around 1% per month. Although Rouwenhorst's study extends to the UK, the

UK sample is restricted to 494 stocks, and apart from controlling for size (an analysis that confirms the original results) there is no detailed analysis of the possible risks of UK momentum returns. There is no other published study of momentum strategies for the UK. Fama and French (1996) suggest that out-of-sample tests of momentum strategies on international data are desirable, to establish whether US evidence is the result of data snooping (Fama and French, 1996, p. 81). This study attempts to fill this gap, by examining medium-term momentum strategies on a large sample of UK stocks over the period January 1977 to June 1998.

An analysis of momentum strategies provides additional evidence on the informational efficiency of the UK stock market. In particular, it offers evidence on the ability of the UK stock market to impound information in the short- to medium-term. If momentum profits exist, the UK stock market fails the basic test of weak-form efficiency, since past returns predict future returns. A study of momentum strategies also aims to improve our understanding of how UK stock prices respond to particular types of information. If momentum profits exist and cannot be explained by market-wide information, then they imply stock prices that only gradually impound either industry- or firm-specific information. This is an important consideration for event studies of firm-specific announcements. A positive finding would also stimulate further research into which types of firm-specific information the market only gradually impounds, with potential implications for accountants and financial analysts as well as investors.

Our study provides a comprehensive test of the profitability of momentum strategies in the UK stock market. We test for the presence of momentum profits using the approaches of both Lehmann (1990) and Jegadeesh and Titman (1993). We conduct this analysis for the period 1977 to 1998 on both a comprehensive sample of UK stocks and on a restricted sample of stocks with suitable accounting data available. This analysis shows that significant momentum profits are available in the UK over the sample period. An analysis of sub-period results, seasonal effects, and the persistence of momentum profits confirms the robustness of the results. Bootstrap tests of significance suggest that the results are robust to any skewness bias[11] or higher order moment non-normality in momentum returns.

We go on to examine the sources of momentum profits by investigating the relation between momentum profits and factors known to be associated with differential average returns. The factors we control for are equity capitalisation ('size'), stock price, book-to-market ratio, and cash earnings-to-price ratio. As part of the analysis we apply the Fama–French three-factor model to control for expected returns.

Our analysis confirms the presence of size, price, book-to-market, and cash earnings-to-price effects in UK stock returns. However, crucially for the current study, these effects cannot explain momentum profits: momentum profits are not due to cross-sectional variation in unconditional mean returns of individual stocks. We also confirm that neither serial correlation in common factor realisations nor delayed stock price reaction to common factor realisations can explain momentum profits. Our conclusion is that the momentum effect is an important, independent phenomenon in UK stock returns and the likely cause is a delayed response to either industry- or firm-specific information.

The paper proceeds as follows. The following section describes the study sample, data, and research methodology. Section 3 reports results on the presence of momentum profits for both the full sample of companies and for the sub-sample of companies that have additional accounting data available. This includes a set of sub-period results, an analysis of seasonality, and an examination of whether momentum profits persist outside twelve-month ranking and holding periods. Section 4 investigates the possible sources of momentum profits, reporting the results of controlling for alternative sources of risk suggested by recent contributions to the literature. The final section summarises the results, offers conclusions, and suggests avenues for further research.

2. SAMPLE, DATA, AND RESEARCH METHODOLOGY

The reference point for the sample is the London Share Price Database (LSPD) over the 20-year period January 1977 to December 1996. From 1975, the LSPD covers all stocks quoted on the London Stock Exchange. However, to control for the possible short-term market microstructure effects documented in earlier US and UK studies, the return data are based on weekly Datastream figures. Therefore, the main sample includes all LSPD stocks that also have price data on Datastream. This results in the exclusion of 689 stocks and a main sample of 4,182 stocks. While it is impossible to state unequivocally whether excluding these stocks imparts any bias to the current study, the sample of 4,182 stocks includes dead as well as live stocks, and the robustness of results on an 'accounting' sub-sample, reported below, increases confidence in its representativeness. Weekly share price data cover the period January 1977 to June 1998.

(i) Data

The basic data consist of Wednesday stock prices. Using weekly Wednesday prices eliminates the Monday effect and reduces holiday effects and the end-of-month effect. Stock return for week τ_w is calculated as:

$$r_{\tau_w} = \frac{P_{\tau_w} + d_{\tau_w} - P_{\tau_w - 1}}{P_{\tau_w - 1}}, \qquad (2)$$

where P_{τ_w} is the date τ_w ex-dividend adjusted Datastream price and d_{τ_w} is the gross dividend in period τ_w adjusted to the same basis as P_{τ_w}. Calculating returns requires both adjusted and unadjusted prices for the early part of the period. This is because Datastream does not record detailed dividend payments before 1988. Therefore, for the period to December 1987, the dividend data come from the LSPD. This entails some further reconciliation since Datastream and the LSPD differ on their precise definitions of capitalisation adjustments and dividends. For example, Datastream records some LSPD (capital distribution) dividends as capitalisations, and the treatment of liquidation distributions and capital repayments, classed as dividends by the LSPD, are unclear in Datastream. A careful analysis of LSPD dividends from January 1977 to December 1987 for the study sample indicates 75 instances where the dividend classification is unclear. An examination of Datastream's adjusted and unadjusted prices and adjustment factors around the ex-dates of these 75 cases shows that Datastream treats these as capitalisations in only seven instances. The appropriate corrections or adjustments are made to LSPD dividends, which are included in equation (2). For the post-1987 period, adjusted dividends come from Datastream.

A decision also has to be made about returns on stocks that delist during the holding period of any strategy. Stocks whose LSPD death type is 7, 14, 16, 20, or 21[12] are assigned a return of -1 in the delisting week;[13] for other death types (such as acquisition, takeover, merger, etc.) the return is set to 0.[14]

Other data collected are as follows:

> *MV* is a stock's equity capitalisation, popularly referred to as size, and used to examine the size effect.
> *UP* is a stock's unadjusted price, used to examine the low-price effect.
> *B/M* is a stock's book-to-market equity value, where book value is equity capital and reserves minus total intangibles. *B/M* is used to examine whether momentum profits are attributable to distinguishing value from growth stocks, and also to control for differences in the cross-section of expected returns given by the FamaFrench three-factor model.
> *C/P* is a stock's cash earnings-to-price ratio. This is calculated as the inverse of Datastream's price-to-cash earnings ratio, where cash earnings are earned for ordinary less ordinary dividend, plus depreciation and deferred tax. *C/P* is also used to examine whether momentum profits are attributable to distinguishing value from growth stocks.

In calculating both *B/M* and *C/P*, book value and cash earnings are for the latest financial year ending at least six months before the date for price or market value. This is to allow for the lag between companies' financial year-ends and reporting dates.[15]

(ii) Methodology

There are various approaches to testing return predictability in the literature (for reviews see Kaul, 1996; and Campbell, Lo, and MacKinlay, 1997). However, a popular approach is to examine specific trading strategies. The intuition for price momentum strategies is that stock prices underreact to information. Therefore, buying past winners and selling past losers will realise significant profits, as the information that has been partially impounded into prices to produce the past winners and losers, continues to be absorbed, generating the price momentum. To provide consistency and comparability, this study constructs similar trading strategies to Jegadeesh and Titman (1993). We consider ranking periods of $r = 3$, 6, 9, and 12 months and subsequent holding periods of $h = 3$, 6, 9, and 12 months, giving a total of 16 $r \times h$ momentum strategies. We also consider two sets of such strategies, one where the holding period follows immediately on the ranking period, the other where the strategies skip one week between holding and ranking periods. The latter is designed to avoid any short-term market microstructure effects that might affect the results. Unlike Jegadeesh and Titman's study, where portfolios involve overlapping test periods, this study examines non-overlapping test periods. This gives $int[(258 - r)/h]$ non-overlapping test periods for each $r \times h$ momentum strategy.

For each $r \times h$ strategy, an eligible stock must have at least r months plus two weeks return data at the beginning of each test period. This ensures that a stock can be held for at least one week for strategies that skip a week between holding and ranking periods. Holding period returns are recorded for decile portfolios and for winner minus loser $(W - L)$ portfolios.

To select stocks for different portfolios, at the start of each holding period, t, the ranking period r-month buy-and-hold return for each qualifying stock is computed as:

$$R_{i,\,t-r:\,t-1} = \prod_{\tau_w = t - r_w}^{t-1} (1 + r_{i\tau_w}) - 1, \tag{3}$$

where $r_{i\tau_w}$ is the return on stock i in week τ_w and r_w is the number of weeks in the ranking period. For most of the analysis, stocks are grouped into ten portfolios according to their ranking period returns. A corresponding buy-and-hold return, $R_{i,\,t:\,t+h}$, is calculated for each stock over the relevant holding period and equally-weighted decile portfolio returns are calculated.[16] The study also examines the profits to the momentum strategy of buying the highest decile (winner) portfolio and selling the lowest decile (loser) portfolio. As well as holding period returns, subsequent parts of the study also require non-overlapping monthly returns for each decile portfolio over the 252 test period months of the full 258-month sample period for $r \times h$ strategies where $r = h$.

We also conduct a preliminary analysis to examine whether an arbitrage opportunity may exist, based on Lehmann's (1990) weighting scheme and classification of winner and loser stocks. The winner (loser) portfolio comprises those stocks whose ranking period returns exceed (are less than) the ranking period return of a within-sample equally-weighted market index. A portfolio that buys past winners and sells past losers is then formed with weights:

$$w_{i,\,h:\,t-r} = \frac{R_{i,\,t:\,t-r} - R_{m,\,t:\,t-r}}{\sum\limits_{R_{i,\,t:\,t-r} - R_{m,\,t:\,t-r} > 0} R_{i,\,t:\,t-r} - R_{m,\,t:\,t-r}} \tag{4}$$

attached to each stock, i, at time t for holding period h, based on ranking period r. This produces an arbitrage portfolio with a stake of £1 in both the long and short sides at the start of the holding period. The profits to this strategy are given by:

$$\pi_{t+h} = \sum_{i=1}^{N_t} w_{i,\,h:\,t-r} R_{i,\,t:\,t+h}, \tag{5}$$

where N_t is the number of eligible stocks at the beginning of the holding period. The returns to the separate winner and loser portfolios are given by corresponding calculations. As shown by Lehmann (1990), equation (5) facilitates an analysis of the sources of profits by breaking them down into three components: (i) those due to time-series predictability of an equally-weighted market index; (ii) those due to time-series predictability of the individual stocks; and (iii) those due to cross-sectional variation in unconditional mean returns of individual stocks.

Given the use of non-overlapping observations, standard t- and F-tests are used to test the significance of mean portfolio returns over the sample period and to test the significance of mean returns across portfolios. As a robustness check against the presence of non-normalities in momentum returns we also provide a bootstrapped analysis of the significance of momentum returns to $r \times h$ strategies where $r = h$ for the full sample and for the accounting sample.

3. INITIAL EVIDENCE ON THE MOMENTUM EFFECT

This section reports the results of momentum strategies applied to the full sample of 4,182 stocks and to a sub-sample of 2,434 stocks with accounting data available. This includes an analysis of Lehmann's (1990) weighting scheme and an analysis of decile portfolio returns. We also report on results for sub-periods, the presence of seasonality effects, the persistence of momentum profits, and robustness checks for non-normalities in this section.

(i) Lehmann's Weighting Scheme

Table 1 presents the average returns of winner, loser, and winner minus loser portfolios for the 16 $r \times h$ strategies, using Lehmann's portfolio weights. Columns 4–7, under Panel A, show the results when the holding period follows on immediately from the ranking period; columns 8–11, under Panel B, show the results when there is a one-week gap between the holding and ranking periods. The returns or profits are for an h-month holding period.

The remarkable result from Table 1 is that the profits to each of the 16 $W - L$ portfolios in both Panel A and Panel B are positive, and all are significantly positive with the one exception of the 3×3 no-gap strategy. It is also evident that imposing a one-week gap between the holding and ranking periods has little effect on profits. Restricting attention to Panel A, the highest profits for 3- and 6-month holding periods follow 12-month ranking periods and the highest profits for 9- and 12-month holding periods follow 6-month ranking periods. The highest annualised profits are for the 12×3 strategy, with an annual return of 19.5% (or 19.5 pence per £1 stake long and short).

(ii) Profits to Decile Winner Minus Loser Portfolios

Table 2 reports returns for decile winner, loser, and winner minus loser portfolios for the same strategies as in Table 1. The numbers of observations are not shown, but are identical to Table 1, and the final column shows the correlation between momentum profits in Panels A of Tables 1 and 2. The results in Table 2 are very similar to those in Table 1, which is not surprising given that Lehmann's portfolio weights place the largest stakes, positive or negative, in stocks with extreme performance in the ranking

Table 1

Average Returns Using Lehmann's Portfolio Weights

Strategy	*Portfolio*	*Obs*	*Return*	*t-stat*	*Min*	*Max*	*Return*	*t-stat*	*Min*	*Max*
			Panel A				**Panel B**			
3 × 3	*W*	85	0.069	5.94	−0.378	0.336	0.069	5.89	−0.363	0.405
	L	85	0.051	3.86	−0.267	0.569	0.041	3.34	−0.259	0.302
	W − L	85	0.018	1.79	−0.693	0.119	0.028	4.59	−0.213	0.113
3 × 6	*W*	42	0.127	4.87	−0.303	0.524	0.128	4.75	−0.312	0.473
	L	42	0.087	2.92	−0.273	0.655	0.090	2.84	−0.288	0.755
	W − L	42	0.040	2.55	−0.390	0.204	0.038	2.13	−0.469	0.202
3 × 9	*W*	28	0.223	4.53	−0.270	1.113	0.224	4.43	−0.279	1.144
	L	28	0.126	2.65	−0.289	0.861	0.127	2.67	−0.314	0.869
	W − L	28	0.097	4.76	−0.133	0.282	0.097	4.84	−0.133	0.275
3 × 12	*W*	21	0.272	5.18	−0.176	0.711	0.275	5.04	−0.167	0.696
	L	21	0.177	3.49	−0.260	0.564	0.180	3.47	−0.241	0.591
	W − L	21	0.096	3.97	−0.137	0.335	0.096	3.83	−0.161	0.367
6 × 3	*W*	84	0.070	5.93	−0.415	0.345	0.069	5.80	−0.402	0.405
	L	84	0.043	3.40	−0.280	0.389	0.035	2.81	−0.283	0.376
	W − L	84	0.027	2.98	−0.433	0.144	0.034	4.46	−0.183	0.148
6 × 6	*W*	42	0.145	5.48	−0.290	0.754	0.144	5.48	−0.255	0.775
	L	42	0.092	3.42	−0.252	0.646	0.078	2.83	−0.340	0.608
	W − L	42	0.053	2.75	−0.352	0.230	0.066	3.89	−0.324	0.222
6 × 9	*W*	28	0.217	6.93	−0.131	0.553	0.216	6.73	−0.135	0.554
	L	28	0.103	2.98	−0.382	0.468	0.106	2.97	−0.377	0.483
	W − L	28	0.114	6.03	−0.097	0.255	0.110	5.62	−0.109	0.247
6 × 12	*W*	21	0.322	5.45	−0.153	0.892	0.321	5.38	−0.147	0.869
	L	21	0.177	3.68	−0.194	0.798	0.162	2.98	−0.295	0.806
	W − L	21	0.145	4.07	−0.157	0.562	0.159	4.95	−0.148	0.517
9 × 3	*W*	83	0.075	6.38	−0.421	0.331	0.074	6.32	−0.400	0.387
	L	83	0.038	3.16	−0.293	0.367	0.033	2.65	−0.295	0.358
	W − L	83	0.037	4.89	−0.295	0.168	0.042	6.48	−0.176	0.158
9 × 6	*W*	41	0.147	5.61	−0.364	0.567	0.147	5.39	−0.367	0.511
	L	41	0.066	2.34	−0.278	0.547	0.069	2.31	−0.292	0.638
	W − L	41	0.082	5.48	−0.194	0.217	0.078	4.90	−0.197	0.222
9 × 9	*W*	27	0.219	4.92	−0.217	0.754	0.218	4.87	−0.209	0.772
	L	27	0.137	2.78	−0.244	0.837	0.127	2.37	−0.261	0.932
	W − L	27	0.082	3.14	−0.287	0.303	0.091	3.31	−0.353	0.307
9 × 12	*W*	20	0.306	4.24	−0.337	1.095	0.305	4.00	−0.346	1.193
	L	20	0.200	2.45	−0.324	1.120	0.208	2.42	−0.338	1.140
	W − L	20	0.105	2.86	−0.257	0.354	0.098	2.46	−0.345	0.357
12 × 3	*W*	82	0.080	6.70	−0.429	0.331	0.079	6.54	−0.408	0.379
	L	82	0.035	2.91	−0.287	0.358	0.030	2.41	−0.286	0.354
	W − L	82	0.046	5.86	−0.253	0.186	0.050	7.06	−0.178	0.188
12 × 6	*W*	41	0.159	5.84	−0.284	0.713	0.158	5.89	−0.249	0.716
	L	41	0.076	2.86	−0.245	0.614	0.068	2.48	−0.335	0.590
	W − L	41	0.083	4.65	−0.230	0.305	0.090	5.33	−0.218	0.288
12 × 9	*W*	27	0.225	4.63	−0.325	1.028	0.225	4.46	−0.336	1.081
	L	27	0.113	2.33	−0.267	0.837	0.114	2.40	−0.290	0.834
	W − L	27	0.112	3.84	−0.269	0.431	0.111	3.77	−0.279	0.425
12 × 12	*W*	20	0.275	6.11	−0.168	0.620	0.274	6.02	−0.177	0.597
	L	20	0.173	3.19	−0.343	0.785	0.173	3.24	−0.346	0.765
	W − L	20	0.102	2.66	−0.277	0.463	0.101	2.65	−0.293	0.484

Table 1 (Continued)

Notes:
The winner (W), loser (L), and momentum ($W - L$) portfolios are constructed based on the past r-month stock returns. The strategy divides all stocks into two groups, winners and losers, depending on whether the past r-month buy-and-hold returns of individual stocks are greater than the past r-month return of the within-sample equally-weighted market index. The money (weight) invested in each stock is given by equation (4). For each $r \times h$ strategy and portfolio the table reports portfolio average h-month holding-period returns (Return) over the sample period, t-statistics (t-stat), minimum return (Min), maximum return (Max), and the number of observations (Obs). Panel A shows the results for portfolios formed without skipping a week between ranking and holding periods. Panel B presents the corresponding results when skipping a week between ranking and holding periods. The sample period is January 1977 to June 1998.

period. Most correlations are over 90% and all are over 80%. All the $W - L$ profits are now significantly positive, and the 12×3 strategy remains the most profitable with an annual return of 23.3%. This matches exactly the results of Jegadeesh and Titman (1993), who find that the 12×3 strategy is also the most profitable for the US, with an annualised return of 16.9%. It also matches the international momentum result of Rouwenhorst (1998) who finds a return of 17.5% to a 12×3 strategy. The results in Panels A and B are again almost identical, indicating that short-run market microstructure effects have no effect on the results. Accordingly, we focus on holding periods that follow on immediately from ranking periods from now on.

(iii) Transactions Costs

The previous analysis ignores transactions costs. The non-overlapping momentum strategies analysed are not transactions intensive. The trading frequency is every h months for an $r \times h$ strategy and some stocks retain their status as winners or losers over successive holding periods. Assuming transactions costs of 0.5% does not affect the momentum profits. For example, applying 0.5% transactions costs to the 6×6 strategy in Panel A leaves six-month momentum profits of 6.4% ($t = 2.83$).

(iv) Momentum Effects for the Accounting Sample

Section 4 below provides a detailed examination of the possible sources of momentum profits. This requires restricting attention

Table 2

Average Returns of Decile Winner (*W*), Loser (*L*) and Momentum (*W–L*) Portfolios

Strategy	Portfolio	Return	t-stat	Min	Max	Return	t-stat	Min	Max	Corr
		Panel A				Panel B				
	W	0.069	5.85	−0.373	0.371	0.069	5.77	−0.357	0.443	
3×3	L	0.044	3.22	−0.323	0.398	0.036	2.53	−0.305	0.374	
	$W-L$	0.025	2.90	−0.403	0.128	0.034	4.61	−0.284	0.135	0.900
	W	0.133	5.10	−0.299	0.527	0.134	5.03	−0.301	0.532	
3×6	L	0.077	2.19	−0.317	0.797	0.079	2.13	−0.333	0.932	
	$W-L$	0.056	2.86	−0.551	0.230	0.055	2.45	−0.667	0.228	0.923
	W	0.235	4.51	−0.270	1.265	0.239	4.46	−0.275	1.289	
3×9	L	0.116	2.02	−0.333	1.028	0.116	2.05	−0.354	1.035	
	$W-L$	0.119	4.82	−0.206	0.344	0.122	5.04	−0.202	0.326	0.813
	W	0.279	5.29	−0.165	0.745	0.284	5.16	−0.161	0.730	
3×12	L	0.170	2.86	−0.320	0.651	0.172	2.81	−0.296	0.648	
	$W-L$	0.109	3.91	−0.202	0.258	0.112	3.94	−0.216	0.275	0.893
	W	0.075	6.51	−0.400	0.324	0.075	6.43	−0.387	0.383	
6×3	L	0.035	2.48	−0.344	0.418	0.028	1.92	−0.340	0.406	
	$W-L$	0.041	4.41	−0.348	0.179	0.047	5.63	−0.198	0.172	0.917
	W	0.152	5.81	−0.282	0.706	0.153	5.85	−0.249	0.735	
6×6	L	0.078	2.43	−0.314	0.754	0.065	2.00	−0.378	0.708	
	$W-L$	0.074	3.27	−0.455	0.329	0.088	4.17	−0.417	0.306	0.914
	W	0.237	7.69	−0.114	0.534	0.237	7.61	−0.115	0.533	
6×9	L	0.077	1.87	−0.475	0.557	0.080	1.90	−0.466	0.580	
	$W-L$	0.160	6.42	−0.091	0.360	0.157	6.16	−0.129	0.351	0.867
	W	0.322	5.86	−0.137	0.778	0.322	5.75	−0.134	0.789	
6×12	L	0.155	2.65	−0.288	0.921	0.143	2.24	−0.361	0.924	
	$W-L$	0.168	5.23	−0.143	0.475	0.179	5.60	−0.135	0.462	0.804
	W	0.080	6.82	−0.399	0.341	0.080	6.77	−0.378	0.380	
9×3	L	0.033	2.32	−0.352	0.439	0.026	1.78	−0.352	0.434	
	$W-L$	0.047	4.99	−0.351	0.213	0.054	6.45	−0.167	0.205	0.937
	W	0.161	6.00	−0.332	0.604	0.160	5.79	−0.336	0.546	
9×6	L	0.051	1.48	−0.358	0.675	0.055	1.50	−0.365	0.791	
	$W-L$	0.110	5.80	−0.256	0.350	0.106	5.09	−0.338	0.371	0.919
	W	0.236	5.25	−0.180	0.871	0.235	5.23	−0.175	0.875	
9×9	L	0.128	2.12	−0.317	1.060	0.115	1.75	−0.342	1.17	
	$W-L$	0.108	3.05	−0.500	0.388	0.120	3.14	−0.580	0.419	0.926
	W	0.330	4.38	−0.298	1.241	0.328	4.20	−0.312	1.274	
9×12	L	0.203	1.95	−0.379	1.451	0.213	1.96	−0.390	1.471	
	$W-L$	0.127	2.55	−0.429	0.481	0.115	2.07	−0.555	0.482	0.922
	W	0.084	6.81	−0.410	0.358	0.083	6.72	−0.391	0.413	
12×3	L	0.030	2.10	−0.345	0.450	0.022	1.49	−0.352	0.442	
	$W-L$	0.054	5.45	−0.339	0.219	0.061	6.78	−0.170	0.201	0.919
	W	0.165	5.99	−0.277	0.760	0.162	5.98	−0.241	0.765	
12×6	L	0.070	2.13	−0.318	0.776	0.058	1.75	−0.398	0.746	
	$W-L$	0.095	4.19	−0.360	0.326	0.104	4.79	−0.347	0.311	0.940
	W	0.239	4.78	−0.302	1.127	0.236	4.55	−0.311	1.175	
12×9	L	0.089	1.54	−0.324	0.969	0.091	1.60	−0.344	0.963	
	$W-L$	0.149	4.76	−0.251	0.418	0.145	4.69	−0.246	0.399	0.915
	W	0.279	6.52	−0.178	0.671	0.276	6.38	−0.185	0.659	
12×12	L	0.161	2.56	−0.408	0.869	0.161	2.61	−0.410	0.833	
	$W-L$	0.119	2.89	−0.318	0.390	0.115	2.89	−0.327	0.397	0.880

Table 2 (Continued)

Notes:
At the beginning of each holding period, qualifying stocks are sorted in ascending order based on their ranking period returns. An equally-weighted portfolio of stocks in the highest decile comprises the winner portfolio (W) and is held long, while an equally-weighted portfolio of stocks in the lowest decile comprises the loser portfolio (L) and is sold short. For each $r \times h$ strategy, these portfolios' average h-month returns (Return), t-statistics (t-stat), minimum return (Min), and maximum return (Max) are summarised in this table. Panel A shows the results of portfolios formed without skipping a week between ranking and holding periods. Panel B shows the corresponding results when skipping a week between ranking and holding periods. The final column reports the correlation coefficients between momentum profits from Table 2, Panel A and decile momentum profits in Panel A above. The sample period is January 1977 to June 1998.

to stocks for which accounting data on book-to-market and cash-to-price ratios are available. The analysis excludes financial firms, stocks listed on the USM or the AIM, third market companies, and OTC companies, according to LSPD classifications. We refer to this sample of 2,434 stocks as the *accounting* sample. To increase our confidence in the wider applicability of this analysis, it is important to confirm first that the results on momentum profits for the full sample are repeated for this sub-sample.

To confirm that the accounting sample gives results consistent with the full sample, Table 3 summarises for this sample the results corresponding to Panels A of Tables 1 and 2. Panel A shows average returns or profits using Lehmann's portfolio weights, while Panel B shows corresponding figures using decile portfolios. The columns headed *No+* show the number of positive outcomes over the sample period for each strategy. All average returns in Table 3 are positive and statistically significant. The proportion of positive holding period momentum profits for each strategy ranges from 68% to 85%. The results in Table 3 mirror the results for the full sample in Tables 1 and 2, suggesting that evidence of momentum profits is not crucially dependent on the particular study samples. The most profitable momentum strategy remains the 12×3 strategy, which returns an annualised 24.0%.

Although momentum profits in Table 3 differ across different ranking periods for a given holding period, the hypothesis that the profits are equal across r for any h cannot be rejected. For example, the F-statistic computed under the null that the momentum returns of each of the $r \times 6$ strategies are jointly

Table 3

Average Returns for the Accounting Sample

Strategy	Portfolio	Return	t-stat	No+	Return	t-stat	No+	Obs
		Panel A			**Panel B**			
	W	0.071	6.06		0.075	6.50		85
3×3	L	0.044	3.78		0.041	3.05		85
	$W - L$	0.026	4.43	61	0.033	4.62	58	85
	W	0.141	5.17		0.148	5.39		42
3×6	L	0.096	3.32		0.084	2.58		42
	$W - L$	0.045	3.74	30	0.064	4.25	32	42
	W	0.230	4.82		0.242	5.15		28
3×9	L	0.146	3.14		0.142	2.50		28
	$W - L$	0.084	4.10	23	0.101	4.87	23	28
	W	0.281	5.40		0.301	5.59		21
3×12	L	0.120	3.66		0.189	2.99		21
	$W - L$	0.081	2.76	16	0.111	3.43	17	21
	W	0.075	6.54		0.079	6.85		84
6×3	L	0.039	3.26		0.034	2.56		84
	$W - L$	0.037	5.83	65	0.045	5.62	64	84
	W	0.149	5.92		0.158	6.29		42
6×6	L	0.083	3.25		0.080	2.63		42
	$W - L$	0.066	4.60	31	0.078	4.54	32	42
	W	0.231	7.10		0.244	7.36		28
6×9	L	0.121	3.28		0.113	2.59		28
	$W - L$	0.109	5.45	22	0.131	5.26	22	28
	W	0.346	5.56		0.348	6.10		21
6×12	L	0.174	3.08		0.167	2.54		21
	$W - L$	0.172	4.64	18	0.181	5.62	18	21
	W	0.077	6.55		0.083	7.06		83
9×3	L	0.036	3.09		0.033	2.38		83
	$W - L$	0.040	6.67	65	0.050	6.29	62	83
	W	0.157	5.74		0.171	6.09		41
9×6	L	0.076	2.77		0.066	1.98		41
	$W - L$	0.081	5.65	34	0.105	6.11	34	41
	W	0.242	5.43		0.258	5.82		27
9×9	L	0.130	2.73		0.121	2.13		27
	$W - L$	0.112	4.39	23	0.137	4.23	22	27
	W	0.324	4.31		0.337	4.45		20
9×12	L	0.207	2.55		0.200	2.20		20
	$W - L$	0.117	3.62	17	0.137	3.29	16	20
	W	0.085	7.07		0.086	7.11		82
12×3	L	0.033	2.81		0.031	2.26		82
	$W - L$	0.052	7.53	64	0.055	6.24	65	82
	W	0.166	6.35		0.166	6.52		41
12×6	L	0.074	2.85		0.075	2.41		41
	$W - L$	0.093	5.55	34	0.091	4.52	31	41
	W	0.244	4.87		0.239	4.83		27
12×9	L	0.123	2.68		0.106	2.02		27
	$W - L$	0.121	3.80	23	0.133	4.49	23	27
	W	0.306	6.59		0.281	6.74		20
12×12	L	0.185	3.57		0.183	3.16		20
	$W - L$	0.121	2.92	15	0.098	2.54	15	20

Table 3 (Continued)

Notes:
The table reports the average *h*-month returns (Return), for 16 strategies, of winner (W), loser (L) and momentum ($W - L$) portfolios. Panel A summarises the results obtained using Lehmann's portfolio weights, and Panel B reports the corresponding results using decile portfolios. *No+* denotes the number of positive outcomes over the sample period for each strategy. The sample period is January 1977 to June 1998.

equal is 0.783 with a *p*-value of 0.51. This justifies focusing attention on strategies where $r = h$ from now on. To make the presentation tractable, we further restrict attention to the 6×6 strategy. This gives comparability with Jegadeesh and Titman (1993) and Chan et al. (1996). However, an examination of the full set of 16 strategies shows that the results for the 6×6 strategy are clearly representative.

(v) Sub-periods, Seasonalities, and Persistence

In this sub-section we report in the text on three further analyses of the momentum profits in the accounting sub-sample. These are a sub-period analysis, an investigation of seasonality effects, and an examination of the persistence of momentum profits.

To check whether the previous results might be period specific, we perform an analysis of decile portfolio returns for the 6×6 strategy for two 11-year sub-periods. These are January 1977 to December 1987 and July 1987 to June 1998.[17] The results show that the momentum effect of the previous section is not due to any particular period. Momentum profits in the two 11-year sub-periods are both significantly positive. The average annualised profits of the $W - L$ portfolio are 15.1% ($t = 3.01$) for January 1977 to December 1987 and 17.4% ($t = 3.33$) for July 1987 to June 1998. Profitability across all deciles is much lower in the second sub-period, but this has no effect on the relative winner minus loser performance results (and even slightly strengthens them).

Many empirical studies have documented the presence of a January effect in stock returns. For example, Rozeff and Kinney (1976) report that returns are higher in January than in any other month in the US. Gultekin and Gultekin (1983) examine monthly stock returns for 17 countries and find that average

January returns are significantly higher than returns in the remaining months for 13 of the 17 countries analysed. Recently, Clare and Thomas (1992 and 1995) report the presence of January, March, and April effects in the UK stock market. It is therefore important to exclude seasonality as a possible explanation of the momentum effect. We therefore examine the average returns in each calendar month for the decile and momentum portfolios for the 6×6 strategy.[18] The analysis reveals strong seasonal patterns. With two marginal exceptions, each decile portfolio achieves its highest return in January.[19] Perhaps more surprising, it is the loser portfolio that shows the largest January decile return of 7.1%. A February effect is also pronounced, with the first or second highest return being realised in this month by nine decile portfolios. March and April are also strong performance months with the returns in these months exceeding the returns in subsequent months for most portfolios. All the *F*-statistics confirm the significance of differences in average returns across calendar months. However, the important message for the current study is that seasonal effects do not explain momentum profits. In fact, the momentum portfolio achieves positive profits in all months except January, so that profits are higher after excluding January. Momentum profits are significantly positive in May, June, July, September, November, and December.

The overreaction hypothesis suggests that winners and losers over a three-year ranking period will switch to become losers and winners, respectively, over two- to three-year holding periods. We examine this effect, using overlapping ranking and holding periods, for the 6×6 momentum strategy, forming decile portfolios semi-annually based on a 6-month ranking period and examining the returns to these decile portfolios over the past $r = 36$ months and over holding periods of $h = 12$, 24, and 36 months.[20] Extending the ranking period to three years gives results that are consistent with 6-month ranking period returns. For $r = 36$, average returns increase monotonically from loser to winner portfolios. The average 3-year ranking period returns to the momentum portfolio are 227%. This shows the presence of backward persistence.[21] However, there is only partial support for mean-reversion as the holding period is extended. There is evidence of mean-reversion for the lowest three deciles, but

$W - L$ momentum profits remain positive over 2- and 3-year holding periods, although insignificantly so in the latter case.[22] Nevertheless, from comparing the 6×12 momentum profits with those for a 6×24 or 6×36 strategy, it is clear that momentum profits in years 2 and 3, in isolation, are negative. This evidence of negative momentum profits in years 2 and 3 indicates that the momentum portfolio profits for holding periods up to one year are not due to differences in unconditional mean returns of the selected stocks.

(vi) Robustness Against Non-normalities

Recent studies examining stock performance over long horizons have documented a positive skewness bias in long-horizon abnormal returns, resulting in standard parametric significance tests being misspecified (Barber and Lyon, 1997; and Lyon, Barber, and Tsai, 1999). Our analysis is based on the difference in returns to winner and loser portfolios over intermediate-horizons and may be less subject to non-normality biases. However, to check that our results on momentum profits are not biased by non-normalities in returns we apply a bootstrap analysis to the momentum profits from the full and accounting samples for strategies $r \times h$ where $r = h$. The precise approach that we follow is the bootstrap shift method (Noreen, 1989). Specifically, for each W, L, and $W - L$ portfolios we conduct a 50% re-sampling, with replacement, from the original samples of portfolio returns and calculate the mean return. This exercise is repeated 10,000 times. We then compute the overall mean return of these 10,000 re-samples and subtract this from each individual mean return. Finally, we rank the mean-shifted 10,000 mean returns. The bootstrapped p-values for our original W, L, and $W - L$ portfolio returns are given according to where these figures fall in the distribution of ranked mean-shifted mean returns. This approach should be robust to any form of non-normality provided only that the bootstrapped sampling distribution fairly represents the shape of the sampling distribution under the null hypothesis. Table 4 reports the results of this analysis. Significance levels are reduced in every case in comparison with significance levels associated with the t-statistics given in Tables 2 and 3 and shown as p-values in columns 4 and 7 of Table 4.[23] However, the crucial result for the present analysis is

Table 4

Bootstrapped *p*-values for the Full and Accounting Samples

Strategy	*Portfolio*	*Return*	*Parametric p-value*	*Bootstrapped p-value*	*Return*	*Parametric p-value*	*Bootstrapped p-value*
		Panel A: Full Sample			**Panel B: Accounting Sample**		
	W	0.069	0.0000	0.0000	0.075	0.0000	0.0000
3×3	L	0.044	0.0009	0.0119	0.041	0.0015	0.0162
	$W - L$	0.025	0.0024	0.0107	0.033	0.0000	0.0006
	W	0.152	0.0000	0.0002	0.158	0.0000	0.0000
6×6	L	0.078	0.0097	0.0495	0.080	0.0059	0.0344
	$W - L$	0.074	0.0011	0.0042	0.078	0.0000	0.0003
	W	0.236	0.0000	0.0002	0.258	0.0000	0.0001
9×9	L	0.128	0.0215	0.0692	0.121	0.0210	0.0672
	$W - L$	0.108	0.0025	0.0067	0.137	0.0001	0.0002
	W	0.279	0.0000	0.0000	0.281	0.0000	0.0000
12×12	L	0.161	0.0091	0.0369	0.183	0.0024	0.0153
	$W - L$	0.119	0.0044	0.0105	0.098	0.0095	0.0191

Notes:
The table reports the average *h*-month returns (Return) and bootstrapped *p*-values (*p*-value), for 4 $r \times h$ strategies where $r = h$, of winner (W), loser (L) and momentum ($W - L$) portfolios. Panel A summarises the results obtained for the full sample, and Panel B reports the corresponding results for the accounting sample. The Return columns repeat figures in Tables 2 and 3. The parametric *p*-value columns report *p*-values corresponding to the *t*-statistics in Tables 2 and 3. The sample period is January 1977 to June 1998.

that momentum profits remain clearly significant, giving *p*-values of less than 1% in most cases and a highest value of 1.91%.

4. THE SOURCES OF MOMENTUM PROFITS

This section provides a detailed analysis of possible risk explanations for the momentum profits of the accounting sample. We examine the characteristics of beta, *MV*, *UP*, *B/M*, and *C/P* for all decile and momentum portfolios. We then investigate the effect of controlling for risk using the Fama–French three-factor model. Finally, we examine the effect of conditioning on *MV*, *UP*, *B/M*, and *C/P*. However, we begin with a restricted analysis of risk characteristics for the full sample.

(i) Decile Returns and Risk Characteristics for the Full Sample

Table 5 gives a detailed breakdown of returns to the decile portfolios and profits to the $W - L$ portfolio for $r = h$ strategies applied to the full sample. From Table 2 these strategies are reasonably representative, although they do not generate the most significant momentum profits.[24] As a preliminary analysis of whether momentum profits are due to cross-sectional differences in mean returns to stocks in the winner and loser portfolios, the table also reports each portfolio's holding period beta, *MV*, and *UP*. Portfolio betas are holding period Scholes–Williams betas estimated using holding period monthly returns and the within-sample value-weighted market index. Portfolio *MV*s and *UP*s are cross-sectional and time-series averages. Figure 1 graphs the decile portfolio returns for each strategy.

The results in Table 5 and Figure 1 show a near monotonic increase in average returns from loser to winner portfolio.[25] The winner portfolio gives the highest returns for each strategy and the loser portfolio and decile 2 give the lowest returns for two strategies each. Portfolio betas and standard deviations follow a rough U-shape across portfolios, but the loser portfolio always has a higher standard deviation than the winner portfolio and has a higher beta in all but the 9×9 strategy. This suggests that neither total risk nor systematic risk can explain the momentum profits. Looking at the average firm size of decile companies for each strategy, winners have the third or fourth lowest *MV*s,

Figure 1

Decile Portfolio Returns

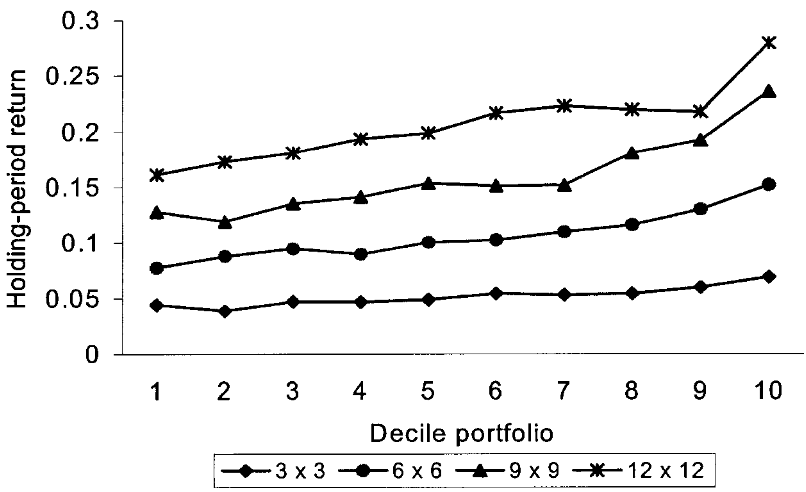


Table 5

Performance and Characteristics of Decile Portfolios for the Full Sample

Strategy	*Portfolio*	*Return*	*Std*	*t-stat*	*Beta*	*MV*	*UP*	*Obs*
	L	0.044	0.128	3.22	1.125	79.50	95.23	85
	$D2$	0.039	0.099	3.63	1.024	145.64	165.03	85
	$D3$	0.047	0.088	4.96	0.894	176.89	183.18	85
	$D4$	0.047	0.088	4.94	0.940	205.71	204.52	85
	$D5$	0.049	0.087	5.21	0.926	227.44	210.17	85
3×3	$D6$	0.055	0.090	5.58	0.966	249.31	211.31	85
	$D7$	0.053	0.089	5.50	0.930	260.32	222.23	85
	$D8$	0.055	0.090	5.60	0.955	273.24	219.89	85
	$D9$	0.060	0.096	5.80	1.004	280.10	233.24	85
	W	0.069	0.109	5.85	1.041	162.02	224.98	85
	$W-L$	0.025	0.079	2.90	−0.084	82.52	129.75	85
						(2.97)	(6.37)	
	L	0.078	0.207	2.43	1.084	64.34	104.60	42
	$D2$	0.088	0.166	3.41	0.973	133.58	133.68	42
	$D3$	0.095	0.155	3.95	0.932	171.42	170.30	42
	$D4$	0.090	0.135	4.29	0.833	197.80	184.12	42
	$D5$	0.100	0.137	4.77	0.975	213.79	222.79	42
6×6	$D6$	0.102	0.134	4.96	0.950	263.29	201.30	42
	$D7$	0.110	0.136	5.25	0.958	252.49	244.32	42
	$D8$	0.116	0.134	5.61	0.953	289.76	241.04	42
	$D9$	0.130	0.145	5.83	1.020	279.16	221.17	42
	W	0.152	0.169	5.81	1.047	183.64	237.99	42
	$W-L$	0.074	0.147	3.27	−0.037	119.30	133.39	42
						(2.82)	(3.67)	
	L	0.128	0.314	2.12	1.059	46.30	81.71	27
	$D2$	0.119	0.241	2.57	1.074	116.86	130.37	27
	$D3$	0.135	0.205	3.42	0.948	180.36	195.11	27
	$D4$	0.141	0.194	3.78	0.933	212.86	190.67	27
	$D5$	0.153	0.180	4.43	0.876	210.31	194.40	27
9×9	$D6$	0.151	0.183	4.30	0.941	252.84	236.11	27
	$D7$	0.156	0.190	4.14	0.939	257.04	230.40	27
	$D8$	0.180	0.189	4.96	0.968	296.86	233.50	27
	$D9$	0.192	0.207	4.82	0.979	261.41	264.00	27
	W	0.236	0.234	5.25	1.084	156.58	236.06	27
	$W-L$	0.108	0.185	3.05	0.024	110.29	154.36	27
						(3.30)	(7.92)	
	L	0.161	0.281	2.56	1.132	56.06	69.29	20
	$D2$	0.173	0.257	3.00	0.986	100.92	114.43	20
	$D3$	0.181	0.196	4.12	0.951	172.29	157.93	20
	$D4$	0.193	0.173	5.00	0.957	206.91	173.64	20
	$D5$	0.199	0.170	5.22	0.946	227.85	191.68	20
12×12	$D6$	0.217	0.168	5.77	0.894	225.19	196.65	20
	$D7$	0.223	0.151	6.61	0.965	241.59	265.01	20
	$D8$	0.220	0.152	6.47	0.964	299.25	288.34	20
	$D9$	0.218	0.137	7.13	0.997	247.80	223.30	20
	W	0.279	0.192	6.52	1.106	165.52	235.45	20
	$W-L$	0.119	0.184	2.89	−0.026	109.45	166.16	20
						(2.41)	(8.28)	

Notes:
The table summarises the decile portfolios' average h-month returns (Return) and their standard deviations (Std), t-statistics (t-stat), Scholes–Williams betas (Beta), average market values in £m (*MV*) and average unadjusted prices (*UP*) for 3×3, 6×6, 9×9, and 12×12 strategies. The final row in each strategy repeats the profits for the $W-L$ momentum strategy from Table 3. Numbers in parenthesis are t-statistics for the $W-L$'s *MV* and *UP*. $D2$ stands for the second decile portfolio, $D3$ for the third decile portfolio and so on. The sample period is from January 1977 to June 1998.

suggesting a small-firm effect could be present. However, losers always have the smallest decile *MV*s, ruling out a positive size effect as an explanation of momentum profits. These results on market values are based on average *nominal* equity capitalisations over the full sample period and could be dominated by later test periods due to the effects of inflation. We therefore repeated the analysis by first standardising each market value by the median market value across stocks in the particular test period. This analysis gave the same pattern of (standardised) *MV*s and similar significance levels for *MV*s of $W - L$ portfolios as those reported in Table 5. The penultimate column of Table 5 shows that stocks in the loser portfolio have the lowest price, while the prices of winner stocks are similar to the prices of stocks in portfolios *D*5 to *D*9. The *t*-statistics show that the prices of winner stocks are significantly greater than the prices of loser stocks. This suggests that momentum profits are unlikely to be due the low-price effect documented by Ball, Kothari and Shanken (1995) for the case of contrarian profits.

(ii) Characteristics of Decile and Momentum Portfolios for the Accounting Sub-sample

Table 6 describes each decile and momentum portfolio's average *h*-month abnormal return, beta, *MV*, *UP*, *B/M*, and *C/P* for the 3×3, 6×6, 9×9, and 12×12 strategies based on the accounting sub-sample. The average *h*-month decile abnormal return is calculated as:

$$\overline{AR}_D = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{n_{D,t-1}}\sum_{i=1}^{n_{Dt}}(R_{i,\,t:\,t+h} - R_{m,\,t:\,t+h}) \qquad (6)$$

where $R_{i,\,t:\,t+h}$ and $R_{m,\,t:\,t+h}$ are the holding period buy-and-hold returns for stock i and for the within-sample value-weighted market index, n_{Dt} is the number of stocks in decile portfolio D at the beginning of the holding period, and T is the number of holding periods of length h in the sample period. The results of the analysis are insensitive to the alternate use of market-model-adjusted abnormal returns, CAPM-adjusted abnormal returns, or multifactor-model-adjusted abnormal returns. Profits to the momentum portfolio, $W - L$, are not affected by the market adjustment to abnormal returns. Betas are ScholesWilliams betas

Table 6

Portfolio Performance and Characteristics for the Accounting Sample

Strategy	*Portfolio*	AR_D	*t-stat*	*Beta*	*MV*	*UP*	*B/M*	*C/P*
	L	−0.006	−0.64	1.149	81.17	92.99	1.757	0.020
	D2	−0.007	−0.95	1.018	154.70	158.85	1.475	0.133
	D3	−0.001	−0.16	0.975	221.30	183.91	1.391	0.130
	D4	−0.002	−0.31	0.945	232.98	213.82	1.277	0.134
	D5	0.001	0.16	0.943	308.37	226.68	1.256	0.149
3 × 3	*D6*	0.005	0.86	0.953	317.14	240.00	1.198	0.162
	D7	0.006	1.18	0.947	320.43	218.10	1.035	0.151
	D8	0.010	1.74	0.987	304.61	237.89	1.032	0.154
	D9	0.014	2.33	1.049	272.39	238.71	1.042	0.153
	W	0.027	3.81	1.034	156.37	211.85	1.034	0.128
	W − L	0.033	4.62	−0.115	75.20	118.86	−0.723	0.108
					[2.53]	[5.55]	[−4.17]	[6.55]
	F10	2.43 (0.01)			9.15 (0.00)	6.72 (0.00)	4.92 (0.00)	14.05 (0.00)
	F8	1.27 (0.26)			4.17 (0.00)	2.51 (0.00)	3.29 (0.00)	1.46 (0.18)
	L	−0.014	−0.58	1.116	74.14	84.05	1.712	−0.009
	D2	−0.011	−0.52	0.994	140.71	168.42	1.621	0.136
	D3	−0.005	−0.31	0.921	219.50	166.75	1.512	0.139
	D4	−0.011	−0.77	0.912	232.22	215.44	1.265	0.139
	D5	0.008	0.56	0.961	264.74	198.10	1.214	0.156
6 × 6	*D6*	0.014	1.10	0.960	309.89	218.86	1.176	0.157
	D7	0.019	1.57	0.971	325.88	216.83	1.165	0.157
	D8	0.025	2.00	0.959	348.84	281.10	1.014	0.158
	D9	0.041	3.07	1.065	291.99	218.31	1.013	0.164
	W	0.064	4.34	1.076	152.10	255.11	0.837	0.131
	W − L	0.078	4.54	−0.040	77.96	171.06	−0.875	0.140
					[2.13]	[4.05]	[−3.69]	[5.75]
	F10	2.60 (0.01)			5.28 (0.00)	4.09 (0.00)	3.29 (0.00)	11.54 (0.00)
	F8	1.58 (0.14)			2.59 (0.01)	1.97 (0.06)	2.44 (0.02)	0.70 (0.67)
	L	−0.015	−0.34	1.058	51.86	85.66	1.892	−0.034
	D2	−0.000	−0.001	1.039	124.05	123.92	1.675	0.115
	D3	−0.014	−0.54	0.967	203.45	210.94	1.539	0.140
	D4	−0.001	−0.05	0.941	251.36	184.42	1.194	0.152
	D5	0.005	0.24	0.961	286.05	197.07	1.239	0.152
9 × 9	*D6*	0.013	0.62	0.925	310.63	208.96	1.064	0.154
	D7	0.041	1.67	1.013	301.69	228.37	1.144	0.156
	D8	0.047	2.37	0.988	334.98	279.55	1.188	0.161
	D9	0.066	2.96	0.995	277.27	289.13	0.920	0.152
	W	0.122	4.61	1.096	141.45	235.58	0.676	0.141
	W − L	0.137	4.23	0.039	89.59	149.92	−1.216	0.175
					[2.79]	[7.13]	[−3.13]	[4.95]
	F10	2.53 (0.008)			4.07 (0.00)	3.25 (0.00)	3.05 (0.00)	10.55 (0.00)
	F8	1.38 (0.22)			1.78 (0.09)	1.92 (0.07)	2.18 (0.04)	1.03 (0.41)
	L	−0.001	−0.02	1.167	44.06	71.81	1.670	−0.029
	D2	0.003	0.06	1.018	124.10	118.06	1.847	0.122
	D3	0.000	0.007	0.970	198.45	153.96	1.949	0.134
	D4	−0.012	−0.37	0.920	278.76	169.21	1.293	0.152
	D5	0.020	0.59	0.976	295.61	190.87	1.283	0.161
12 × 12	*D6*	0.038	1.07	0.994	286.66	283.17	1.095	0.169
	D7	0.045	1.53	0.975	348.92	214.94	1.085	0.168
	D8	0.041	1.64	0.991	309.27	315.12	1.099	0.161
	D9	0.078	2.84	0.993	235.22	236.43	1.037	0.164
	W	0.097	3.09	1.111	167.99	237.40	0.656	0.139
	W − L	0.098	2.54	−0.056	123.93	165.59	−1.014	0.168
					[2.55]	[6.45]	[−2.61]	[3.54]
	F10	0.94 (0.49)			2.95 (0.00)	2.95 (0.00)	2.81 (0.00)	7.16 (0.00)
	F8	0.69 (0.68)			1.43 (0.20)	1.96 (0.06)	2.65 (0.01)	1.14 (0.34)

Table 6 (Continued)

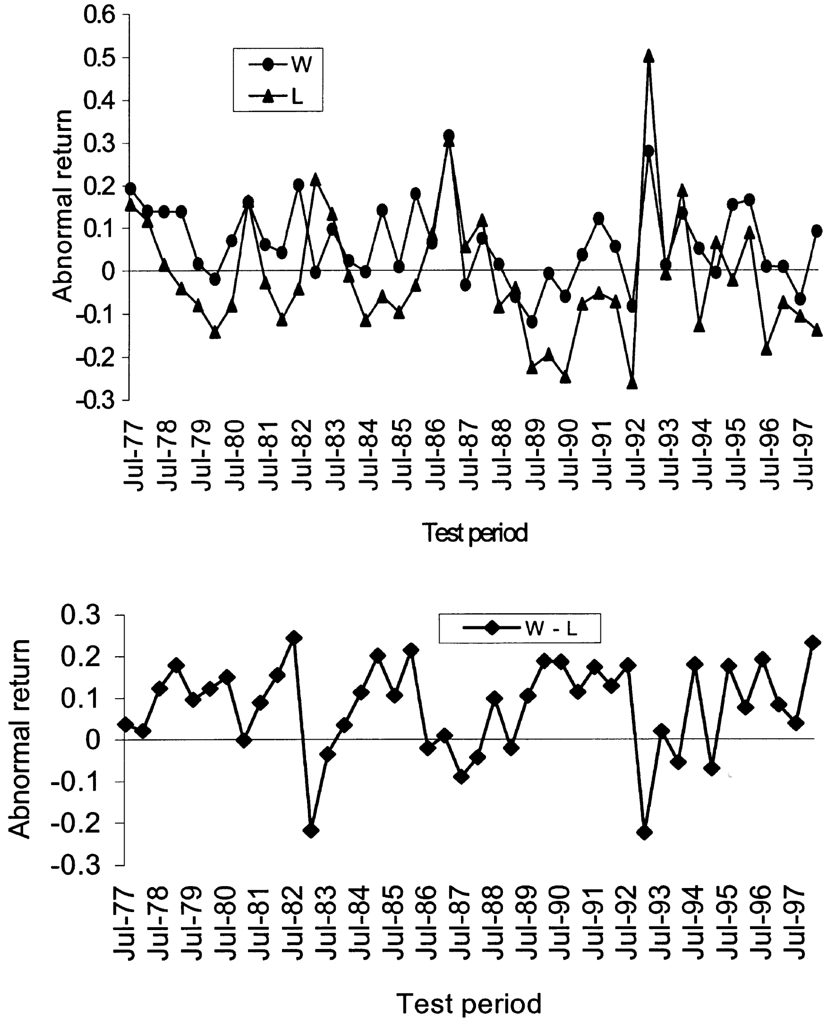
Notes:
The decile portfolios are sorted based on *r*-month buy-and-hold ranking period returns. The lowest decile is the loser (*L*), and the highest decile is the winner (*W*). This table summarises the average *h*-month market-adjusted abnormal returns ($\overline{AR}_D$) of each decile portfolio and the decile momentum portfolio for the 3×3, 6×6, 9×9, and 12×12 strategies. Each decile portfolio's average market value in £m (*MV*), Scholes-Williams beta (Beta), average *UP*, *B/M*, and *C/P* are also reported in this table. Numbers in square brackets are *t*-statistics for a momentum portfolio's *MV*, *UP*, *B/M*, and *C/P*. *F10*s are *F*-statistics, computed under the null hypothesis that for each $r \times h$ strategy the average abnormal returns (or average *MV*, *UP*, *B/M*, or *C/P*) on loser (*L*) through winner (*W*) are jointly equal. *F8*s are *F*-statistics computed under the null hypothesis that for each $r \times h$ strategy the average abnormal returns (or average *MV*, *UP*, *B/M*, or *C/P*) on *D*2 through *D*9 are jointly equal. Numbers in parenthesis following the *F*-statistics are *p*-values for the *F*-statistics. The sample period is January 1977 to June 1998.

based on holding period monthly returns against the value-weighted market index.

Table 6 shows that the patterns of each portfolio's return performance, beta, *MV*, and *UP* for the accounting sample are the same as those in Table 5 for the full sample. The winner deciles have significantly positive abnormal returns, while the loser deciles have negative, though insignificant, abnormal returns. The fact that this result is robust to alternative ways of measuring abnormal returns means that momentum profits are principally due to winners rather than losers.[26] In Table 6 the *F*-statistics, computed under the null hypothesis that for each $r \times h$ strategy the average abnormal returns on *D*2 through *D*9 are jointly equal are all statistically insignificant, while the *F*-statistics, computed under the null that the average abnormal returns of loser (*L*) through winner (*W*) are jointly equal are all statistically significant, except for the 12×12 strategy. Figure 2 plots the abnormal returns for the *W*, *L*, and $W - L$ portfolios in each of the 42 individual holding periods of the overall sample period for the strategy 6×6. Figure 2 shows that using market-adjusted return as the measure of abnormal return results in momentum profits that are not riskless.[27] An investor initiating a momentum strategy in test periods beginning in January 1983 or in January 1993 would not have been impressed with the outcome. However, it must be remembered that these are returns adjusted only for market movements. The remainder of this section examines in more detail whether or not momentum profits can be explained by alternative risk factors.

Figure 2

Market-adjusted Abnormal Returns for the 6 × 6 Strategy



In Table 6, the pattern of portfolio betas exactly matches the pattern for the full sample in Table 5. Systematic risk cannot, therefore, explain the momentum profits for the accounting sample. While both winner and loser portfolios tend to select smaller firms, the effect is far more pronounced for the latter. *MV* for portfolio *W* is more than twice *MV* for portfolio *L* for the

6×6, 9×9, and 12×12 strategies, and it is 1.93 times larger for the 3×3 strategy. The t-statistics show that these differences in market values are significant. Similar to the full sample results in the previous sub-section, this suggests that a positive size effect cannot explain momentum profits for the accounting sample. A more complete analysis of the size effect is provided below by the Fama–French three-factor model.

UP is lowest for the loser portfolios and generally increases in moving up the deciles, though this effect is, not surprisingly, more evident as the holding period increases. This pattern suggests that momentum profits are unlikely to be related to the low-price effect.

An interesting feature of Table 6 is that the patterns for *B/M* and *C/P* are not consistent. *C/P* is lowest for loser portfolios and significantly less than *C/P* for winner portfolios. However, *C/P* for the winner portfolio is either first or third lowest after the loser portfolio. This suggests that the relation between momentum profits and *C/P* ratios is not strong.[28] In contrast, *B/M* ratios decrease almost monotonically from loser to winner portfolios, with the loser's *B/M* ratio being significantly greater than the winner's. These results indicate that winner stocks tend to be growth stocks and loser stocks tend to be value stocks. These findings are similar to those documented by Chan et al. (1996, p. 1689) for the US market:

> The portfolio of past losers contains stocks with relatively depressed past earnings and cash flow, while the portfolio of past winners contains glamour stocks that have done well in the past.

They also correspond with international evidence on value versus growth stocks found by Fama and French (1998) for a sample including a limited number of UK stocks. This evidence of glamour winners and value losers suggests the momentum profits are unlikely to be due to the *B/M* effect.

(iii) Numbers of Small, Low-price, High C/P, and High B/M Stocks in Decile Portfolios

As an alternative way of examining the effects of size, price, *C/P*, and *B/M* on portfolio returns, Table 7 reports the average number of small stocks (Small-*MV*), low-price stocks (Low-*UP*), high *C/P* stocks (High-*C/P*), and high *B/M* stocks (High-*B/M*)

Table 7

Numbers of Small Stocks, Low-price Stocks, High *C/P* Stocks, and High *B/M* Stocks in the Decile Portfolios

	L	*D2*	*D3*	*D4*	*D5*	*D6*	*D7*	*D8*	*D9*	*W*	*+No*
					Panel A (1/3 breakpoint)						
Small-*MV*	68.24	51.74	45.17	39.24	38.57	34.31	32.00	32.67	33.26	41.57	3
	(0.164)	(0.124)	(0.108)	(0.094)	(0.093)	(0.082)	(0.077)	(0.078)	(0.080)	(0.100)	
Low-*UP*	81.00	55.57	45.12	37.348	35.45	32.45	30.26	28.40	30.83	37.60	2
	(0.196)	(0.134)	(0.109)	(0.091)	(0.086)	(0.078)	(0.073)	(0.069)	(0.074)	(0.091)	
High-*C/P*	37.98	44.90	45.14	43.48	42.74	41.43	39.19	37.74	39.57	34.45	14
	(0.093)	(0.110)	(0.111)	(0.107)	(0.105)	(0.102)	(0.096)	(0.093)	(0.097)	(0.085)	
High-*B/M*	58.60	52.69	45.33	42.52	39.83	36.52	32.79	30.31	29.14	24.40	2
	(0.149)	(0.134)	(0.116)	(0.108)	(0.102)	(0.093)	(0.084)	(0.077)	(0.074)	(0.062)	
					Panel B (1/5 breakpoint)						
Small-*MV*	45.95	31.83	28.60	23.55	21.88	20.29	18.26	18.10	17.83	23.12	4
	(0.184)	(0.128)	(0.115)	(0.094)	(0.088)	(0.081)	(0.073)	(0.073)	(0.072)	(0.093)	
Low-*UP*	58.24	34.00	27.00	21.86	19.67	17.29	15.86	15.90	16.57	20.93	1
	(0.236)	(0.138)	(0.109)	(0.088)	(0.079)	(0.070)	(0.064)	(0.064)	(0.067)	(0.085)	
High-*C/P*	26.90	28.90	26.55	26.19	24.83	23.24	22.38	20.95	23.10	20.36	11
	(0.111)	(0.119)	(0.109)	(0.108)	(0.102)	(0.096)	(0.092)	(0.086)	(0.095)	(0.084)	
High-*B/M*	41.57	33.67	27.38	24.74	23.00	21.02	17.74	17.14	15.33	13.10	2
	(0.177)	(0.144)	(0.117)	(0.105)	(0.098)	(0.090)	(0.076)	(0.073)	(0.065)	(0.056)	

Notes:
The decile portfolios of the 6×6 strategy are formed based on 6-month past returns and held for 6 months. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (*L*); the equally-weighted portfolio of stocks in the next decile is portfolio *D2*; and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (*W*). The average numbers of small stocks (Small-*MV*), low-price stocks (Low-*UP*), high *C/P* stocks (High-*C/P*) and high *B/M* stocks (High-*B/M*) in the decile portfolios over the 42 holding periods are reported. The last column, denoted *+No*, shows the numbers of holding periods in which the number of small stocks, low-price stocks, high-*C/P* stocks, and high-*B/M* stocks in the winner portfolio are greater than in the loser portfolio. Panel A gives results when referring to the 1/3 smallest stocks in the accounting sample as small stocks, the 1/3 lowest-*UP* stocks as low-price stocks, the 1/3 highest *C/P* stocks as high-*C/P* stocks, and the 1/3 highest *B/M* stocks as high-*B/M* stocks. Panel B shows the results using quintile (1/5) breakpoints. Numbers in parenthesis are the average numbers of small stocks, low-*UP* stocks, high-*C/P* stocks, and high-*B/M* stocks as proportions of the total small stocks, total low-*UP* stocks, total high-*C/P* stocks, and total high-*B/M* stocks, respectively. The sample period is January 1977 to June 1998.

over the 42 holding periods for the 6×6 strategy. Each cell reports the number for each decile portfolio and the number as a proportion of the relevant population of small stocks, low-price stocks, etc. Panel A defines the relevant population of small stocks at the beginning of each holding period as the one-third of stocks with the smallest *MV*; this one-third breakpoint similarly applies to *UP*, *C/P*, and *B/M*. Panel B reports a corresponding analysis using quintile (one-fifth) breakpoints.

Table 7 confirms that the momentum effect cannot be attributed to a positive size effect, a low price effect, or a high *B/M* effect. From Panel A, the average number of small stocks in the loser portfolio is 68.24, accounting for 16.4% of the total, while it is 41.57 in the winner portfolio, which accounts for 10.0% of the total. Over the 42 holding periods, there are only three periods in which the winner portfolio has more small stocks than does the loser portfolio. This result is generally stronger for the one-fifth breakpoint in Panel B. Similar results hold for the low-*UP* and high-*B/M* rows. The loser portfolio has the highest average number of both low-*UP* and high-*B/M* stocks. From Panel A, the average number of low-*UP* stocks is 81.0 in the loser portfolio and 37.6 in the winner portfolio; the corresponding numbers of high *B/M* stocks are 58.6 and 24.4. There are only two individual holding periods in which this ordering is reversed. Again, the result is stronger for the one-fifth breakpoint.

One unexpected result from Table 7 is that although Table 6 shows the loser portfolio to have the lowest average *C/P* ratio, it actually has a higher average number of high-*C/P* stocks than the winner portfolio. The winner portfolio in fact has the lowest average number of high-*C/P* stocks, although these numbers do not show much variation across the decile portfolios. On balance, these results do not give strong support for the *C/P* effect as an explanation of momentum profits.

(iv) Multifactor Risk Adjustment

The previous analysis shows that the momentum effect cannot be explained by the separate influences of systematic risk, size, or book-to-market value. This section examines whether momentum profits can be accounted for by their joint influence, by using the Fama–French three-factor model. This also allows for a time-varying size effect. Following equation (1) above, the model is estimated as:

$$r_{Pt} - r_{ft} = a_P + b_P(r_{mt} - r_{ft}) + s_P SMB_t + h_P HML_t + \varepsilon_{Pt}, \qquad (7)$$

where r_{Pt} is the return on decile portfolio P in month t, r_{ft} is the one-month Treasury Bill rate for month t, and r_{mt} is the within-sample value-weighted market return in month t.[29] SMB_t is the month t return on the factor-mimicking portfolio for size and HML_t is the month t return on the factor-mimicking portfolio for B/M. The method for constructing SMB_t and HML_t follows Fama and French (1993 and 1996) and is explained in Table 8. If the three-factor model can explain the returns of the decile portfolios, the intercept, a_P, in equation (7) should not be significantly different from zero.[30] Panel A of Table 8 reports the results of equation (7) regressions for each decile portfolio and the momentum portfolio for the 6×6 strategy over the full test period of 252 months. For comparison, Panel B reports estimates of Jensen's alpha and beta from a regression of the CAPM:[31]

$$r_{Pt} - r_{ft} = \alpha_P + \beta_P(r_{mt} - r_{ft}) + e_{Pt}. \tag{8}$$

From Panel A of Table 8, abnormal returns estimated for the three-factor model are smaller than those obtained for the CAPM.[32] This indicates that the three-factor model captures effects omitted by the CAPM. However, controlling for size and B/M does not change the overall pattern in returns reported earlier. The abnormal returns of the loser portfolio are -0.61% per month ($t = -3.35$); abnormal returns are significantly negative for the bottom four decile portfolios. The abnormal returns of the winner portfolio are 0.81% per month ($t = -7.06$); abnormal returns are significantly positive for the top three decile portfolios. The momentum portfolio abnormal profits are 1.42% per month ($t = 6.22$). In addition, loser and winner portfolios still have similar market exposures ($b_L = 1.158$, $b_W = 1.098$). All decile portfolios load significantly positively on SMB_t, and on HML_t except for the winner portfolio ($h_W = -0.057$, $t = -1.14$). This indicates that there is a small-stock effect and a high-B/M effect. The coefficients on SMB_t show that both winner and loser portfolios are loaded heavily on small stocks, with the loser portfolio being more so. The coefficients on HML_t decrease from loser to winner portfolio, the loser portfolio concentrating most heavily on value stocks and the winner portfolio on growth stocks. These results are similar to those of Fama and French (1996) for the US, based on an eleven-month ranking period, though the difference between UK loser and winner portfolio loadings on SMB_t is less and on HML_t is greater. The results in Table 8 are also consistent with the results in Table 6 and indicate that the three-

Table 8

Estimates of the Fama–French Three-factor Model and the CAPM Model for the Decile Portfolios

	L	$D2$	$D3$	$D4$	$D5$	$D6$	$D7$	$D8$	$D9$	W	$W-L$
Panel A											
a_P	−0.0061	−0.0050	−0.0028	−0.0037	−0.0010	0.0002	0.0013	0.0024	0.0044	0.0081	0.0142
	(−3.35)	(−5.08)	(−2.75)	(−4.82)	(−1.42)	(0.27)	(1.61)	(2.80)	(5.01)	(7.06)	(6.22)
b_P	1.158	1.099	0.996	0.964	0.989	1.006	0.995	0.999	1.007	1.098	−0.060
	(27.94)	(48.72)	(43.42)	(55.66)	(61.86)	(55.77)	(52.42)	(52.04)	(49.85)	(41.89)	(−1.15)
s_P	1.061	0.935	0.755	0.700	0.687	0.641	0.643	0.707	0.692	0.894	−0.167
	(19.30)	(31.30)	(24.83)	(30.51)	(32.42)	(26.81)	(25.54)	(27.79)	(25.85)	(25.72)	(−2.42)
h_P	0.605	0.557	0.372	0.357	0.279	0.297	0.163	0.165	0.082	−0.057	−0.662
	(7.64)	(12.94)	(8.49)	(10.78)	(9.14)	(8.61)	(4.50)	(4.49)	(2.12)	(−1.14)	(−6.66)
R^2	0.779	0.912	0.887	0.928	0.940	0.926	0.917	0.917	0.911	0.884	0.153
Panel B											
α_P	−0.0044	−0.0029	−0.0013	−0.0025	−0.0002	0.0013	0.0019	0.0030	0.0040	0.0080	0.0124
	(−1.45)	(−1.26)	(−0.67)	(−1.41)	(−0.11)	(0.80)	(1.15)	(1.73)	(2.20)	(3.54)	(5.09)
β_P	1.152	1.023	0.944	0.938	0.981	0.979	0.988	0.978	1.083	1.097	0.055

Table 6 (Continued)

Notes:
The 6×6 strategy's decile portfolios are formed semi-annually based on 6-month past returns. The Fama-French three-factor model is:

$$r_{Pt} - r_{ft} = a_P + b_P(r_{mt} - r_{ft}) + s_P SMB_t + h_P HML_t + \varepsilon_{Pt},$$

and it is estimated using the ranking-period monthly decile-portfolio returns, r_{Pt}, and the value-weighted monthly market returns, r_{mt}. The average abnormal monthly portfolio returns are estimated by a_P, and r_{ft} is the one-month Treasury Bill rate observed at the beginning of month t. SMB_t is the monthly return on the factor-mimicking portfolio for size (*MV*), and HML_t is the monthly return on the factor-mimicking portfolio for book-to-market (*B/M*). Both SMB_t and HML_t are constructed in the same way as in Fama and French (1993 and 1996). Stocks in the accounting sample are allocated semi-annually to two groups, small (*s*) and big (*b*), based on whether their market values (*MV*s) at the beginning of the sorting period are below or above the median *MV*. The stocks in the accounting sample are allocated in an independent sort to three book-to-market groups, low (*l*), medium (*m*) and high (*h*), based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the values of *B/M*. Six size–*B/M* portfolios (*s/l, s/m, s/h, b/l, b/m, b/h*) are defined as the intersections of the two *MV* and the three *B/M* groups. The value-weighted monthly returns on the six size–*B/M* portfolios are calculated for the subsequent 6 months based on each semi-annual sorting. SMB_t is the difference, each month, between the average of the returns on the three small-stock portfolios (*s/l, s/m* and *s/h*) and the average of the returns on the three big-stock portfolios (*b/l, b/m* and *b/h*). HML_t is the difference, each month, between the average of the returns on the two high-*B/M* portfolios (*s/h* and *b/h*) and the average of the returns on the two low-*B/M* portfolios (*s/l* and *b/l*). Panel A summarises the estimates of the three-factor model. R^2s are adjusted for degrees of freedom. Panel B gives the results estimated for the CAPM. In Panel B, β_P is the Scholes–Williams estimate and α_P is Jensen's performance measure. Numbers in parenthesis are *t*-statistics. The sample period is January 1977 to June 1998.

factor model is appropriate. However, adjusting for the three factors does not eliminate the significant profits earned by the momentum portfolio. Rather it makes the momentum portfolio appear more profitable because of its significant negative loadings on size and *B/M*.

To provide further confirmation of the above results, we re-estimate the three-factor model and re-examine portfolio characteristics in the two 11-year sub-periods examined in Section 3(v). We report on these results only in the text. Although the analysis shows that the portfolio loadings are different in the two sub-periods, the pattern of decile portfolio abnormal returns is unchanged. Momentum profits are significantly positive in both sub-periods, being 1.1% ($t = 3.56$) for January 1977 to December 1987 and 1.26% ($t = 4.26$) for July 1987 to June 1998. Portfolio characteristics (*MV, UP, B/M, C/P*) experience large changes from the first to the second 11-year sub-period, but relative values across decile portfolios within sub-periods are unchanged.

We also repeat the Fama–French regressions including a dummy variable for the month of January to control for the possibility of January returns having an undue influence on the parameter estimates. We report on these results in the text. Not surprisingly, given the results on seasonalities reported in Section 3(v), the January dummy is significantly positive for the loser portfolio and significantly negative for the winner minus loser portfolio. However, including a January dummy produces only marginal changes to parameter estimates given in Table 8 and leaves our previous conclusions intact.

The overall conclusion from these results is that, as in Fama and French (1996), the three-factor model cannot explain the continuation in returns over the intermediate horizon.

(v) Controlling for C/P

Table 6 shows that the winner portfolio's *C/P* ratio is significantly higher than the loser's *C/P* ratio. It is possible that momentum profits are due to winner stocks being high *C/P* stocks. To examine this possibility, we use Zarowin's (1989 and 1990) technique for controlling for size to control for stocks' *C/P* ratios. The procedure is as follows:

1. For any $r \times h$ strategy, sample stocks are sorted in ascending order of *C/P* ratio at the start of each holding period and allocated to five quintile portfolios.
2. Stocks are allocated in an independent sort to five quintile portfolios based on their past *r*-month buy-and-hold returns at the start of each holding period.
3. Four *C/P*–return portfolios are defined as the intersections of the two extreme *C/P* quintiles and the two extreme return quintiles. These are low-*C/P*–loser (*LL*), low-*C/P*–winner (*LW*), high-*C/P*–loser (*HL*), and high-*C/P*–winner (*HW*). The equally-weighted *h*-month holding period returns and the monthly holding period returns on the four *C/P*–return portfolios are calculated for each sorting. The monthly returns are used to estimate the Fama–French three-factor model.
4. Five arbitrage portfolios are constructed based on the four *C/P*–returns portfolios formed in the previous step as follows:

(a) low-*C/P*–winner minus low-*C/P*–loser ($LW - LL$);
(b) high-*C/P*–winner minus high-*C/P*–loser ($HW - HL$);
(c) high-*C/P*–loser minus low-*C/P*–loser ($HL - LL$);
(d) high-*C/P*–winner minus low-*C/P*–winner ($HW - LW$);
(e) high-*C/P*–winner minus low-*C/P*–loser ($HW - LL$).

Note that (a) and (b) are *C/P*-matched arbitrage portfolios; (c) and (d) are return-matched arbitrage portfolios; and (e) is a mixed arbitrage portfolio. Their arbitrage *h*-month returns and monthly returns are directly derived from the four *C/P*–return portfolios.

If the *C/P* effect is the cause of the momentum profits, the two arbitrage portfolios $LW - LL$ and $HW - HL$, which are *C/P*-matched but have disparate return performances, should earn insignificant profits. At the same time, the two arbitrage portfolios $HW - LW$ and $HL - LL$, which are return-matched but have disparate *C/P* ratios, should earn significant returns. If the momentum effect exists the two *C/P*-matched portfolios should continue to earn significant profits.

Table 9 summarises the results for the 6×6 strategy, controlling for the *C/P* effect. Here, *No.* gives the average number of stocks in the four *C/P*–return portfolios and R_6 is the average six-month return over the 42 holding periods. The table also reports the estimates of the Fama–French three-factor model for each portfolio. The results in Table 9 show that the method used to control for *C/P* is not perfect as the *C/P* ratios of the two *C/P*-matched arbitrage portfolios ($LW - LL$ and $HW - HL$) are significantly different from zero. Despite this, the table still gives clear results on the relation between the *C/P* and momentum effects.

The *C/P* effect is distinct. The average 6-month returns of the two high-*C/P*–return portfolios are 24.00% (*HW*) and 17.77% (*HL*), while for the two low-*C/P*–return portfolios they are 8.87% (*LW*) and 2.24% (*LL*). As a result, the two return-matched arbitrage portfolios, $HL - LL$ and $HW - LW$, and the mixed arbitrage portfolio, $HW - LL$, all earn unusually high returns. Their average 6-month arbitrage profits are 15.53% ($t = 8.46$), 15.12% ($t = 6.25$), and 21.75% ($t = 11.22$) respectively.

However, the clear *C/P* effect does not subsume the momentum effect. The average 6-month holding period returns

Table 9

Results After Controlling for the *C/P* Effect

	LL	*LW*	*HL*	*HW*	*LW−LL*	*HW−HL*	*HL−LL*	*HW−LW*	*HW−LL*
No.	77.83	51.29	56.10	43.86	–	–	–	–	–
C/P	−0.316	−0.044	0.448	0.348	0.272	−0.100	0.764	0.393	0.664
	(−8.79)	(−2.58)	(12.66)	(16.65)	(9.00)	(−2.94)	(14.12)	(17.05)	(17.46)
R_6	0.022	0.089	0.178	0.240	0.066	0.062	0.155	0.151	0.218
	(0.65)	(2.95)	(5.81)	(7.99)	(2.62)	(3.31)	(8.46)	(6.25)	(11.22)
a_P	−0.0156	−0.0040	0.0080	0.0198	0.0116	0.0118	0.0236	0.0238	0.0354
	(−8.52)	(−1.99)	(4.30)	(14.04)	(4.46)	(5.02)	(9.84)	(9.69)	(14.60)
b_P	1.191	1.134	1.164	1.056	−0.057	−0.108	−0.028	−0.078	−0.135
	(28.44)	(24.76)	(27.38)	(32.73)	(0.96)	(2.00)	(0.51)	(1.39)	(2.44)
s_P	1.267	1.051	1.078	0.836	−0.216	−0.242	−0.189	−0.215	−0.430
	(22.82)	(17.31)	(19.14)	(19.55)	(−2.73)	(−3.39)	(−2.60)	(−2.88)	(−5.85)
h_P	0.519	−0.136	0.756	0.159	−0.654	−0.597	0.237	0.295	−0.359
	(6.49)	(−1.55)	(9.32)	(2.58)	(−5.76)	(−5.81)	(2.27)	(2.75)	(−3.39)
R^2	0.797	0.738	0.776	0.818	0.126	0.137	0.037	0.054	0.138

Notes:
The table summarises the results for the 6 × 6 strategy, controlling for the *C/P* ratio. At the beginning of each holding period, stocks are ranked in ascending order based on their *C/P* ratios. The first quintile is referred to as low-*C/P* firms, and the fifth quintile as high-*C/P* firms. At the beginning of each holding period, stocks are also independently sorted in ascending order based on their past 6-month returns. The lowest quintile gives the loser portfolio and the highest quintile gives the winner portfolio. Four *C/P*-return portfolios of low-*C/P*–loser (*LL*), low-*C/P*–winner (*LW*), high-*C/P*–loser (*HL*), and high-*C/P*–winner (*HW*) are defined as the intersections of the two extreme *C/P* quintiles and the two extreme return quintiles. The portfolios are equally weighted. In the table, *No.* is the average number of stocks in the portfolios, and R_6 describes the average six-month returns the portfolios earn over the 42 holding periods. The table also reports the estimates of the Fama–French three-factor model:

$$r_{Pt} - r_{ft} = a_P + b_P(r_{mt} - r_{ft}) + s_P SMB_t + h_p HML_t + \varepsilon_{Pt},$$

where a_P is the average monthly abnormal return for portfolio *P*. Numbers in parenthesis are *t*-statistics. R^2s are adjusted for degree of freedom. For detailed description of the three factor model see Table 8. The sample period is January 1977 to June 1998.

of the two *C/P*-matched arbitrage portfolios, $LW - LL$ and $HW - HL$, are significantly positive in spite of the *C/P* ratio of $HW - LW$ being significantly negative. The returns of $LW - LL$ and $HW - HL$ are 6.63% ($t = 2.62$) and 6.22% ($t = 3.31$). This means that winner stocks still significantly outperform loser stocks after controlling for their *C/P* ratios. The results also imply that the momentum strategy does not tend to select more high-*C/P* stocks in the winner than in the loser portfolio. These results are consistent with the results in Table 7.

Finally, adjusting for the Fama–French three-factors after controlling for *C/P* does not eliminate the momentum profits. Instead, the estimates of the Fama–French three-factor model generally confirm the momentum effect and other findings documented earlier. The two *C/P*-matched arbitrage portfolios, $LW - LL$ and $HW - HL$, realise average monthly profits of 1.16% ($t = 4.46$) and 1.18% ($t = 5.02$). Additionally, the patterns of other coefficients are consistent with earlier findings. For example, losers and winners have similar systematic risk exposures with β_L being higher than β_W, and the loser portfolio is more heavily loaded on *SMB* and *HML* than the winner portfolio is. Therefore, adjusting for the market, and size and *B/M* factors does not affect the profitability of the momentum strategy even after controlling for *C/P*. In fact, it accentuates the momentum profits because of the negative coefficient of b_P, s_P, and h_P of the arbitrage portfolios.

(vi) Sub-sample Analysis

This section examines portfolio returns within several sub-samples stratified on *MV*, *UP*, *B/M*, and *C/P*. Twelve sub-samples are analysed: three size-based sub-samples (small-, medium-, and big-*MV*), three price-based sub-samples (low-, medium-, and high-*UP*), three *B/M*-based sub-samples (low-, medium-, and high-*B/M*), and three *C/P*-based sub-samples (low-, medium, and high *C/P*). Each sub-sample contains one-third of the stocks in the accounting sample. This analysis achieves four purposes. First, it offers a direct examination of the size, price, *B/M* and *C/P* effects. Second, it facilitates a further test of previous results. Third, it shows whether momentum profits are confined to particular sub-samples. Fourth, it offers additional evidence on the sources of momentum profits. As argued by Jegadeesh and Titman (1993), if expected returns are related to size, price, *B/M*, and *C/P*, the cross-sectional variation in expected return should be less within these sub-samples than in the parent sample. As a result, momentum profits should be less pronounced within each sub-sample than in the parent sample. On the other hand, if the source of momentum profits is serial correlation in idiosyncratic returns, profits need not decrease when momentum strategies are implemented on these sub-samples.

Table 10 reports the average semi-annual returns for the 6×6 strategy for each of the twelve sub-samples (with *t*-statistics in parenthesis). *F*10, with associated *p*-value, is the *F*-statistic computed under the null hypothesis that within a given sub-sample the average semi-annual returns of the ten decile portfolios are jointly equal. *F*8, with associated *p*-value, is the *F*-statistic computed under the null hypothesis that within a given sub-sample the average semi-annual returns of deciles *D*2 through *D*9 are jointly equal.

The size and low-price effects are evident in Table 10. The returns of the decile portfolios in the small-*MV* sub-sample and in the low-*UP* sub-sample are generally higher than the returns in the medium- and big-*MV* sub-samples and medium- and high-*UP* sub-samples respectively. However, the momentum profits in the small-*MV* sub-sample (4.7%) and low-*UP* sub-sample (2.5%) are lower than in the full accounting sample (7.8%) and both are insignificant. The *F*-statistics show that we cannot reject the hypothesis that the average semi-annual returns of the ten decile portfolios are jointly equal in either of these sub-samples. By contrast, momentum profits in the medium- and big-*MV* sub-samples and in the medium- and high-*UP* sub-samples are significant and are larger than in the full accounting sample. The *F*-statistics reject the joint equality of returns on the ten decile portfolios but fail to reject the joint equality of returns on portfolios *D*2 to *D*9.[33] On balance this evidence shows that momentum profits are not related to firm size or low-price effects.[34]

The results in Panel B of Table 10 tell a similar story. The *B/M* and *C/P* effects are striking. Average semi-annual returns are generally higher for all decile portfolios in the high-*B/M* sub-sample than in either the low- or medium- *B/M* sub-samples, with the exception of the winner portfolio. Average semi-annual returns are uniformly higher for all decile portfolios in the high-*C/P* sub-sample than in either of the other two *C/P* sub-samples. However, the *F*-statistics show that there are no significant differences in the decile portfolio returns in either the high-*B/M* or high-*C/P* sub-samples. The average momentum profits in either sub-sample are smaller than in the full accounting sample and the momentum profits in the high-*B/M* sub-sample are insignificant. In contrast, momentum profits in the low- and medium-*B/M* sub-samples and in the low- and medium-*C/P* sub-samples are statistically significant and they generally exceed the profits of 7.81% for the 6×6 momentum strategy on the full accounting sample. This evidence confirms that momentum profits are not due to the *B/M* and *C/P* effects.

Taken together, these results show that momentum profits are not driven by any particular sub-sample. This indicates that momentum profits are not due to cross-sectional variation in expected stock returns.

Table 10

Size, *UP*, *B/M*, and *C/P* Sub-sample Analysis

Panel A

	Small-MV	*Medium-MV*	*Big-MV*	*Low-UP*	*Medium-UP*	*High-UP*
L	0.114	0.037	0.054	0.107	0.039	0.066
	(2.73)	(1.28)	(2.48)	(2.54)	(1.70)	(3.42)
D2	0.122	0.068	0.084	0.102	0.080	0.081
	(3.92)	(2.65)	(4.64)	(2.97)	(3.48)	(4.84)
D3	0.101	0.077	0.080	0.097	0.102	0.092
	(3.65)	(3.20)	(4.24)	(3.17)	(4.35)	(4.95)
D4	0.107	0.083	0.094	0.109	0.083	0.097
	(3.81)	(3.64)	(5.31)	(3.63)	(3.82)	(5.83)
D5	0.094	0.086	0.088	0.068	0.090	0.093
	(3.43)	(3.85)	(4.95)	(2.54)	(4.59)	(5.22)
D6	0.128	0.105	0.096	0.109	0.109	0.101
	(4.28)	(4.16)	(5.75)	(3.56)	(5.11)	(6.06)
D7	0.153	0.120	0.096	0.123	0.118	0.107
	(5.39)	(5.17)	(4.93)	(3.92)	(5.16)	(5.81)
D8	0.125	0.118	0.113	0.135	0.114	0.116
	(4.36)	(5.18)	(5.48)	(4.27)	(5.07)	(6.26)
D9	0.141	0.134	0.119	0.136	0.130	0.134
	(5.25)	(5.28)	(6.11)	(4.28)	(5.58)	(6.73)
W	0.162	0.158	0.148	0.133	0.168	0.162
	(5.24)	(5.74)	(6.66)	(3.93)	(7.14)	(6.87)
$W - L$	0.047	0.121	0.094	0.025	0.128	0.096
	(1.84)	(6.31)	(4.81)	(1.00)	(7.65)	(5.15)
*F*10	0.53	2.02	1.72	0.41	2.30	2.12
[*p*-value]	[0.854]	[0.036]	[0.083]	[0.929]	[0.016]	[0.027]
*F*8	0.50	0.98	0.54	0.51	0.64	0.84
[*p*-value]	[0.837]	[0.447]	[0.804]	[0.826]	[0.723]	[0.553]

Table 10 (Continued)

Panel B

	Low-B/M	*Medium-B/M*	*High-B/M*	*Low-C/P*	*Medium-C/P*	*High-C/P*
L	0.052	0.063	0.117	0.041	0.071	0.159
	(1.67)	(2.27)	(3.23)	(1.07)	(2.82)	(4.91)
*D*2	0.052	0.084	0.117	0.019	0.072	0.155
	(2.20)	(4.08)	(4.17)	(0.64)	(3.27)	(5.97)
*D*3	0.074	0.091	0.110	0.026	0.091	0.149
	(3.11)	(4.39)	(4.01)	(0.95)	(4.72)	(6.15)
*D*4	0.089	0.099	0.109	0.008	0.091	0.139
	(4.21)	(4.48)	(4.02)	(0.38)	(4.28)	(6.04)
*D*5	0.083	0.098	0.111	0.037	0.094	0.160
	(3.68)	(4.62)	(4.39)	(1.67)	(4.73)	(6.23)
*D*6	0.094	0.115	0.118	0.049	0.105	0.160
	(4.59)	(5.33)	(4.83)	(2.57)	(5.12)	(6.53)
*D*7	0.118	0.109	0.124	0.076	0.096	0.167
	(5.39)	(4.95)	(5.48)	(3.14)	(4.91)	(7.03)
*D*8	0.135	0.105	0.122	0.072	0.105	0.178
	(5.55)	(5.32)	(5.23)	(3.70)	(5.03)	(7.40)
*D*9	0.146	0.132	0.135	0.090	0.130	0.189
	(5.91)	(5.44)	(5.12)	(4.30)	(5.68)	(6.59)
W	0.174	0.143	0.132	0.112	0.153	0.210
	(6.03)	(5.48)	(5.99)	(3.94)	(6.37)	(7.78)
$W - L$	0.122	0.080	0.015	0.070	0.082	0.052
	(4.69)	(4.41)	(0.63)	(2.41)	(5.08)	(2.86)
*F*10	2.74	1.03	0.11	1.70	1.33	0.64
[*p*-value]	[0.004]	[0.413]	[0.999]	[0.088]	[0.221]	[0.759]
*F*8	1.93	0.48	0.12	1.64	0.63	0.41
[*p*-value]	[0.064]	[0.848]	[0.997]	[0.123]	[0.731]	[0.895]

Notes:
The table presents the average semi-annual returns for decile portfolios and the momentum portfolio for the 6 × 6 strategy implemented on various sub-samples. Within each sub-sample, the decile portfolios are formed on the basis of 6-month past buy-and-hold returns and held for 6 months. At the start of each holding period, the stocks in a given sub-sample are ranked in ascending order based on their 6-month past returns. The equally-weighted portfolio of stocks in the lowest past return decile is the loser portfolio (L), the equally-weighted portfolio of stocks in the next decile is denoted as *D*2, and so on. The equally-weighted portfolio of stocks in the highest past return decile is the winner portfolio (*W*). The momentum portfolio is the winner minus the loser portfolio ($W - L$). Panel A reports average semi-annual returns for each portfolio for the three size-based and three price-based sub-samples. Panel B reports the average semi-annual returns for each portfolio for the three *B/M*-based and the three *C/P*-based sub-samples. Numbers in parenthesis are *t*-statistics. *F*10 is the *F*-statistic computed under the null hypothesis that for a given sub-sample the average semi-annual returns of the 10 decile portfolios are jointly equal. *F*8 is the *F*-statistic calculated under the null that for a given sub-sample the average semi-annual returns of portfolio *D*2 through portfolio *D*9 are jointly equal. Numbers in square brackets are *p*-values of the *F*-statistics. The sample period is January 1977 to June 1998.

(vii) Common Factor Related Sources of Momentum Profits

Having dealt with cross-sectional variation in expected returns as a possible explanation of momentum profits, as a final check on the sources of momentum profits we test for serial correlation in common factor realisations and for the presence of a delayed price reaction to a common factor as possible explanations. This analysis follows Jegadeesh and Titman (1993) and we refer the reader to their study for the detail.

Assuming a single-factor return-generating model, Jegadeesh and Titman show that if momentum profits are due to serial correlation in common factor realisations, the within-sample serial covariance of the equally-weighted index is required to be positive. Testing for this relationship on semi-annual index returns formed from the accounting sample gives a first-order autocorrelation of -0.079 with a *t*-statistic of -0.52.

To test for the presence of a delayed price reaction to a common factor we run the following regression:

$$r_{Pt} = a_P + b_P(r_{mt-1} - \mu_m)^2 + e_{Pt}, \tag{9}$$

where r_{Pt} is the holding period return for the 6×6 momentum portfolio formed in month t, r_{mt-1} is the return on the within-sample value-weighted market index for the six months immediately preceding month t, and μ_m is the unconditional mean return on the market index. If a delayed price reaction is the source of momentum profits, then b_P should be positive. If not, and given the negative serial covariance in the market index, b_P should be negative. Running this regression on the same semi-annual index returns formed from the accounting sample gives a significantly negative b_P coefficient of -1.84 with a *t*-statistic of -2.4.

These results show that neither serial correlation in the realisations of a single common factor nor delayed price reaction to a (single) common factor contribute to momentum profits. Combined with the evidence of previous sections, this suggests that the momentum effect is likely to result from market underreaction to either industry- or firm-specific information. These findings are consistent with those for the US market.

4. CONCLUSIONS

We have shown that a momentum effect is present in UK stocks. More important, it is distinct from other systematic effects and established regularities associated with cross-sectional variation in average returns. Controlling separately for systematic risk, size, price, book-to-market ratio, or cash earnings-to-price ratio does not eliminate momentum profits. As in the US, the Fama–French three-factor model, which simultaneously controls for systematic risk, size, and book-to-market, leaves momentum profits intact. Indeed, because of the momentum portfolio's loadings on size and book-to-market its profits are enhanced after adjusting for the Fama–French three-factor model.

Further analysis shows that neither serial correlation in the realisations of a single common factor nor delayed price reaction to common factor realisations can explain momentum profits. An inevitable conclusion is that, as for US stocks, the profitability of momentum strategies is attributable to serial correlation either in industry-specific or idiosyncratic components of stock returns: stock prices show a delayed reaction to industry- or firm-specific information.

The question remains, why is there a momentum effect? The apparent consistency of the momentum profits across different national stock markets reduces the likelihood that the effect is due to data-snooping. The fact that results in this paper closely resemble findings for US stocks points to some generality in investor behaviour as one possible explanation. We have seen that behavioural theories exist that predict medium-term price momentum as a result of systematic departures from the full model of investor rationality. Our findings lend some support to these behavioural theories. However, they cannot qualify as a proper test of these theories. As Fama (1998) points out, a valid test of these theories requires confronting them with evidence on the full set of phenomena they predict.

An alternative, rational explanation for medium-term return continuation, as pointed out by Fama and French (1996), is that the momentum effect indicates a previously undiscovered risk factor. One response would be for event studies covering intermediate horizons, for example those examining stock price behaviour related to seasoned equity offerings (SEOs), takeovers, and stock repurchases, to control for momentum effects.[35]

However, in our view to automatically control for a 'winner minus loser' momentum factor in event studies would be mistaken as at this stage this would prejudge the issue. The momentum effect is really only a symptom of some underlying cause and it is the underlying cause of the effect that requires further analysis. For example, if some identifiable events are generating the momentum in stock returns, controlling indirectly for these would eliminate the true underlying phenomenon: controlling for the symptom would mask the cause. Chan et al. (1996) have already examined the relation between price momentum and earnings momentum effects in US stock returns. As earnings announcements are the most important regular information items that come to the stock market, they are the obvious candidates to consider first as underlying causes of the momentum effect. Earnings announcements should clearly include not only regular interim and preliminary earnings disclosures (and quarterlies where these are present), but also the increasingly common use of profit warnings by companies. This is research we are currently undertaking. Further analysis might then extend to other 'events'. It would also be helpful to distinguish between industry and firm-specific effects in momentum profits; this would cast further light on their source and on whether they compensate for any remaining uncontrolled for risk. Finally, following Kraft (1999), a value-weighted momentum strategy, in contrast to the equal-weighting used in the current study, would allow an assessment of market efficiency as it affects the wealth of the average investor.

NOTES

1 The literature has also examined short-run contrarian strategies using ranking and holding periods of one month or less. Explanation for the profitability of these strategies in the US is generally put down to alternative market microstructure effects (see, for example, Jegadeesh, 1990; Lehmann, 1990; Lo and MacKinlay, 1990; and Jegadeesh and Titman, 1995a and 1995b). Using data for 40 companies over the period 1982–1990, MacDonald and Power (1992) find that continuation rather than reversal characterises weekly returns in the UK.

2 As Jegadeesh and Titman (1993) point out there are earlier studies of so-called *relative strength rules*. These are based on past price performance, but they do not follow the precise investment strategy implemented by Jegadeesh and Titman. For example, Levy (1967) finds a strategy that buys stocks with current prices substantially higher than their average prices over the previous 27 weeks earns significant abnormal returns. Jensen and Bennington (1970), re-examining Levy's strategy, find insignificant results. Jegadeesh and Titman (1993) also point out that Value Line rankings and some mutual fund investment strategies are based partly on relative strength.

3 Jegadeesh and Titman (1993) refer to *the returns of relative strength portfolios* in discussing their own results. Subsequent literature has tended to attach the description *momentum strategy* to their approach.

4 This is the strategy of buying an equally-weighted portfolio of stocks in the highest decile of performance over the previous six months and selling an equally-weighted portfolio of stocks in the lowest decile of performance over the previous six months, and holding these positions for six months. JT use overlapping observations, so this strategy is repeated every month in their sample period.

5 JT examine two forms of their momentum strategy, one where the holding period follows immediately on the ranking period, the other where there is a one-week gap between holding and ranking periods. The latter is designed to avoid the market microstructure effects documented in short-run overreaction studies. The figure of 1.49% is for the one-week gap version; without the gap the figure is 1.31%. For the 6×6 strategy the figures are similar.

6 These figures are not strictly returns as they correspond to zero-investment, arbitrage portfolios with one monetary unit of stocks bought on the long side and one monetary unit of stocks sold on the short side of the momentum strategy. Following the majority of the literature, we refer to percentage returns to describe the profits to arbitrage portfolios.

7 The results of CJL are supported by the results of Bernard, Thomas and Wahlen (1997), who adopt a variant of the Jegadeesh–Titman portfolio formation strategy. They find a link between price and earnings momentum and conclude that some results on return momentum point to clear mispricing while other results point to a strategy involving considerable risk.

8 Conrad and Kaul examine the period 1926–1989 but find momentum profits are insignificant during the earlier 1926–1947 sub-period.

9 Lewellen and Shanken (1999) show that the presence of estimation risk can result in short-term return momentum even when markets satisfy conventional properties of market efficiency and rational expectations.

10 Hong, Lim, and Stein (1999) attempt to provide an out-of-sample test of the prediction of Hong and Stein's (1999) gradual-information-diffusion model that momentum should be greater in stocks where information gets released more slowly. They find that momentum profits generally vary inversely with firm size and are greater for stocks with low analyst coverage, the latter effect being more pronounced for bad news.

11 See Lyon and Barber (1997) and Lyon, Barber and Tsai (1999).

12 These death types correspond to: liquidation, quotation cancelled for reason unknown, receiver appointed/liquidation, in administration/administrative receivership, and cancelled assumed valueless.

13 Although this may increase the likelihood of finding a momentum effect for loser stocks, we feel this is the most reasonable rule to adopt for these death

types. We checked the sensitivity of our results to assigning delisting returns of 0 to these death types. Although momentum profits are slightly reduced as expected, the overall results of this paper, in particular the significance of momentum profits, are confirmed.

14 In the case of acquisitions and takeovers, whether stocks are losers or winners may depend crucially on whether the ranking period spans the takeover bid. Assuming a delisting return of zero probably biases the results, on balance, against finding momentum profits.

15 Datastream's *P/C* ratio does not adjust for this time lag. The appropriate adjusted figure is calculated as $(P/C)_{-6}P_0/P_{-6}$ where the -6 subscript refers to a six-month lagged value and the subscript 0 refers to the current date.

16 Where there is a gap between the end of the rank period and the start of the holding period, there is a one week difference between $t-1$ and t.

17 This sub-period analysis also offers a true out-of-sample test of the profitability of a momentum trading strategy in the UK.

18 The analysis is based on weekly returns falling within calendar months.

19 For the two marginal exceptions the January return is demoted to runner-up month only at the third significant digit.

20 Where observations overlap we use Newey–West, heteroskedasticity- and autocorrelation-consistent standard errors.

21 From the viewpoint of informational efficiency, it also shows that subsequent momentum profits, while significantly positive, are dwarfed by the previous price adjustment that triggers the momentum strategy.

22 This should not be interpreted as evidence against the overreaction effect, as the intermediate ranking period used here does not match the long-term ranking period used in overreaction studies.

23 This result suggests that leptokurtosis in returns could be a greater problem than skewness for the current sample.

24 Other $r \times h$ strategies and strategies that skip a week between holding and ranking periods give very similar results. We omit reference to these corresponding results from now on.

25 A conference participant queried the positive returns for loser portfolios in Table 5. It should be remembered that these portfolios comprise stocks that are losers in ranking periods, whereas the returns given here are for subsequent holding periods. In addition these returns are averages across all sample test periods; Table 2 gives an indication of the spread of holding period returns for the full sample in the Min and Max columns.

26 This serves to assuage concerns about the practical difficulty of short-selling loser stocks.

27 In the case of simple market-adjusted abnormal returns, the market adjustment clearly cancels out in calculating momentum profits.

28 Further analysis is carried out below.

29 We report in the text below on a supplementary analysis that includes a dummy variable to control for any January effect.

30 An analogous interpretation applies to the intercept coefficient for the momentum portfolio, a_{W-L}.

31 When estimating equation (8), the value of β_P is the Scholes–Williams beta estimate.

32 The figures for the CAPM are similar to those for market-adjusted abnormal returns and systematic risk in Table 6.

33 For the big-*MV* sub-sample the rejection is at 8%.

34 The fact that momentum profits are larger for the medium- and big-*MV* sub-

samples than for the small-*MV* sub-sample also counters concerns that investors cannot exploit momentum profits due to the larger transactions costs associated with small firms.

35 Carhart (1997) augments the Fama–French three-factor model with a momentum factor when analysing the persistence of mutual fund performance in the US.

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