The Vanishing Abnormal Returns of Momentum Strategies and 'Front-Running' Momentum Strategies

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We find variations in returns from momentum strategies. Unlike most studies, we form portfolios one week prior to the end of month, called 'front-running' momentum portfolios. As expected, due to the effects of institutional momentum trading, our 'front-running' portfolios generate returns of similar magnitude but lower volatility than month-end strategies. We also show that the previously documented large-firm momentum effect is sensitive to the strategy examined, and is attributable to the abnormal returns of large NASDAQ stocks. Moreover, momentum strategies did not earn significant returns during our sample period, an indication that momentum is not an unambiguously persistent anomaly.

INTRODUCTION

We assess the profitability of momentum strategies in the years since the seminal momentum study of Jegadeesh and Titman (1993). We examine the profitability of momentum strategies in various sub periods and during specific market states to gain a better understanding of the relationship between the strategy and overall market conditions. To this end, we form Jegadeesh and Titman zero-cost momentum strategies using a comprehensive data set that is adjusted for distributions and delistings. We then sort individual portfolio months by the prevailing market condition at the time. Various classifications of market conditions are used as a robustness check. We investigate the structure of momentum returns by examining the returns in size and exchange-based sub samples.

We then investigate whether the widespread use of momentum strategies following the discovery of the momentum effect has had any impact on stock returns. We note that if institutional momentum trading affects month-end stock prices, evaluating a momentum strategy prior to the month-end should generate returns in excess of that achieved by a regular month-end strategy. To this end we construct 'front-running' momentum strategies, strategies that evaluate momentum portfolios five business days before the month-end, but are otherwise identical to their month-end counterparts. To study the 'front-running' effect in greater detail, we investigate a number of sub samples and momentum strategies that prior literature has suggested will be most affected by institutional momentum trading. We then compare the return of these strategies with those of conventional month-end strategies.

In contrast to previous studies, we find that momentum returns are not significant for the entire sample period. We show that this is due to the period during and after the market crash experiencing abnormal momentum returns. In the sample period, momentum is related to stock market movements, but not to movements in the economy as a whole. Interestingly, we find that the large firm momentum effect is not robust to the specification of the ranking period and appears to be driven by the abnormal returns of large NASDAQ stocks within the sample period.

Consistent with institutional momentum trading affecting end of month returns, we find that 'front-running' a momentum strategy generates economically significant returns in excess of a month-end strategy only for small firms. Further the returns of a 'front-running' strategy are consistently less volatile than that of an equivalent month-end strategy. The 'front-running' effect is most pronounced when using a three-month ranking period.

METHODOLOGY

Data

Our data consist of daily stock return data obtained from the Center for Research in Security Prices (CRSP). The sample is then constructed from all stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and NASDAQ stock exchange. To ensure that our results are not distorted by securities with abnormal return behavior, we include ordinary shares and exclude ADRs, REITs, closed-end funds, primes and scores and foreign incorporated companies (see, for example, Hong, et.al, 2000 and Lee and Swaminathan, 2000). We compound the daily returns recorded by CRSP to monthly, thus including all distributions to shareholders. We adjust for split events to ensure that the stock price data is directly comparable at different times during the history of a security. The market capitalization of a stock is then defined as the market value of one stock multiplied by the number of shares outstanding. Market return data, also from CRSP, is defined as the periodic return on the Standard & Poor's 500 Composite Index (S&P500). Finally, we obtain the monthly growth in real Gross Domestic Product, seasonally adjusted at annual rates, from the U.S Bureau of Economic Analysis. Our sample covers the period of December 1990 through to December 2004. Due to our analysis of momentum returns post-1993, the actual sample period used differs according to the momentum strategy (i.e. the length of the ranking and holding periods) employed.

It has been noted that the CRSP database does not report monthly prices or returns for stocks that were delisted in that month. In addition, Shumway (1997) documents a delisting bias in the CRSP database. However, in spite of these problems, delisting biases are rarely examined or addressed in the momentum literature. An exception to this convention is the work of Grundy and Martin (2001), who address the omission problem by eliminating stocks that are delisted after the ranking period but before the end of the holding period. This restriction implicitly assumes that investors possess perfect foresight of delisting, and will not consider investing in such stocks. Grundy and Martin (2001) note that when a winner is delisted, it is generally the result of a merger or takeover. In contrast, stocks within the loser portfolios are typically delisted due to liquidation or other negative performance-related reasons. Given the extensive empirical evidence that the share price of target firms increases substantially from a predefined period before the bid announcement date to the completion of the takeover (see Jensen and Ruback, 1983; Franks and Harris, 1989), it appears that Grundy and Martin's assumption induces a bias against finding momentum returns.

Our usage of the CRSP daily data files removes an element of the bias inherent in the CRSP monthly database. Within the daily data files, daily return data is recorded for securities until they are delisted, with the last recorded daily trading value present in the database. However, when a stock is delisted, any return subsequent to the delisting is still ignored. To address this problem and the consequent bias it generates, we obtain delisting data from CRSP. For each delisted stock, we obtain the "delisting return", which is the return of a security after it is delisted from an exchange. This return is calculated by comparing the security's "amount after delisting" - the value of a security after it delists from an exchange, with its price on the last day of trading. The amount after delisting can itself be the off-exchange price, an off-exchange price quote, or the sum of a series of distribution payments. In our dataset, there are 8,545 stocks that are delisted during the sample period, representing 52.44% of the stocks in the dataset. The large number of delistings in the sample suggests that the CRSP database does not suffer from the survivorship biases that other databases such as the Datastream database experience. Datastream provides dead stock files that can be applied to recreate a complete sample. However, unadjusted and in its raw state, the relative paucity of delistings in the Datastream database indicates that it suffers from survivorship bias.

For each delisted stock, we examine the delisting return and add this to the sample if the date at which the amount after delisting is recorded is within the month the stock is delisted. Where the amount after delisting is recorded after the month the stock is delisted (for our example, in February 2000 or later), we do not include the delisting return in our return calculations, but rather set the monthly return to zero. There are 552 such firms. For these firms, the next available price may not be realized for months if not years and is thus generally highly uncertain.

Shumway (1997) notes that the CRSP data files contain a delisting bias, finding that the CRSP files are missing thousands of delisting returns. The omission of returns from the CRSP database introduces a bias into studies that use the database, as the return of such stocks would be incorrectly calculated using the last trading price. Shumway finds that the delisting bias is primarily concentrated in firms that delist for bankruptcy, insufficient capital and other performance-related reasons, which are generally unanticipated. For such firms, the delisting return is likely to be close to -1. Although our system does not address the issue of delisting bias in its entirety, it does generate a more accurate and realistic dataset and more accurate results. Our system acknowledges the delisting bias inherent in the CRSP database and the uncertainty of delisting returns by assuming that no return is obtained within the month of delisting or after a delisting, if an amount after delisting is not available within the delisting month. As previous research has identified that this delisting bias is concentrated amongst stocks delisted due to negative performance reasons and that these stocks lie primarily within the loser portfolio, we induce a bias against finding momentum returns. Nevertheless, the number of affected stock months is limited, with only 552 stocks not recording a delisting return within the delisting month. If we assume that all of these stocks are liquidated and subsequently worthless, the delisting bias as documented by Shumway (1997) will affect only 0.04% of our sample. Further, the proportion of firms that are subsequently worthless is unlikely to approach 100% of the stocks without immediate delisting returns, and as such, any delisting bias is at best minimal.

The Construction of Momentum Portfolios

The month-end momentum or relative strength portfolios are constructed using the methodology of Jegadeesh and Titman (1993). At the start of each month, the *ranking* or *formation period* return of each stock is calculated as the compounded total return over the past J months. The stocks are hence ranked on:

$$R_{it} = (1 + r_{t-J})(1 + r_{t-(J-1)}) \ldots (1 + r_{t-1}) \tag{1}$$

where r_t is the month t return on stock i and J is the length of the ranking period in months. From the universe of stocks, those that have a return history of at least J months and were actively traded at both the start and end of the formation period are ranked on their formation period return. The restriction of the sample to actively traded stocks does not introduce a bias since all information necessary is known prior to the investment period.

The stocks are then split into deciles, with the best performing decile referred to as the *'winner'* portfolio (P1). Correspondingly, the worst performing decile is referred to as *'loser'* portfolio (P10). Stocks within each portfolio are equally-weighted, and the relative strength or momentum strategies we examine involve subsequently buying the winner portfolio and selling the loser portfolio for a *holding period* of *K* months. As such, the momentum strategies are zero-cost, self-financing strategies.

Previous research (see Jegadeesh, 1990 and Lehmann, 1990) has documented the existence of reversals in the very short-term. To address this, strategies with a one month gap between the ranking and holding periods are also considered. With regards to the specific momentum strategies examined, past research, including that of Jegadeesh and Titman (1993) and Rouwenhorst (1998) show the results of different momentum strategies are quite similar, with average returns of approximately 1 percent per month when a ranking period of 6, 9 or 12 months is used regardless of the length of the holding period. Consequently, we only consider strategies that use either a three-month or six-month ranking period. In all, this yields 16 different strategies.

Consistent with the vast majority of the momentum literature, these momentum strategies all utilize overlapping portfolios, whereby the investment strategy is followed every month, such that at any month *t*, a series of momentum portfolios are held from the previous *k-1* months. In essence, this entails that for every month *t*, the strategy buys the winner portfolio and sells the loser portfolio, as well as closing out the position initiated in month *t-K*. The *k* individual momentum portfolios are equally-weighted within the momentum strategy. Overlapping portfolios are used to increase the power of our tests and allows simple t-statistics to be used. Moskowitz and Grinblatt (1999) argue that the use of overlapping portfolios also reduces the effects of the bid-ask bounce, thereby providing cleaner results. Given the volatility of momentum returns, the use of overlapping portfolios also reduces the volatility of momentum returns.

With the passage of time, the value of the individual momentum portfolios will change, with those portfolios that had performed well during the holding period holding greater value. To address this issue, Jegadeesh and Titman (1993) use a strategy whereby the momentum portfolios are rebalanced monthly so that they continue to be equally weighted. This rebalancing involves selling a proportion of those portfolios with above average performance (relative to the other momentum portfolios) during the portion of the holding period that has elapsed, and using the proceeds to buy the poorer performers. We follow this strategy of monthly rebalancing. As such, the return of the momentum strategy in any month *t* is the average return of the *k* individual momentum portfolios held in that month.

The holding period return of each individual momentum portfolio is calculated as the average of the stocks within the portfolio (as the portfolios are equally-weighted). However, as was noted in the previous section a number of stocks within the sample are delisted during the sample period. Where such stocks are included in momentum portfolios, no additional returns are attributed to that stock for the balance of its holding period. This is the most conservative method of handling a delisting without introducing a selection bias, though it results in a small bias against finding momentum returns.

Momentum and Market States

To examine the pattern of momentum returns, we note that the behavioral models of Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) suggest that higher momentum profits are gained in periods following market gains. The model of Daniel, et al., (1998) suggests that the momentum effect is greater when investor overconfidence is high. To the extent that investor overconfidence is greater in periods following market gains, this suggests greater momentum returns in periods following stock market increases. Hong and Stein (1999) find that decreasing risk aversion leads to greater delayed overreaction and therefore greater momentum profits. If risk aversion decreases as wealth increases, the model of Hong and Stein (1999) also suggests momentum profits are higher in periods following market increases. Cooper, Gutierrez and Hameed (2004) examine the link between momentum profits and market gains, finding that momentum returns depend on the state of the market, with a positive and significant return of 0.93% following an 'up-market' and an insignificant return of -0.37% following a 'down-market'. An up-market is defined by Cooper, et al., (2004) as one where lagged three-year market returns are positive and a down-market as one where lagged three-year market returns are negative.

To examine the relationship between momentum and overall market conditions, we replicate the Cooper, et al., (2004) methodology and classify each month in the sample period using its market state. As our sample period consists of 12 years, the use of lagged 3-year returns will result in the state of the market (henceforth the market state) to be defined in relation to one-quarter of the sample period. In addition, the use of a shorter timeframe may be more appropriate to capture the market state in the volatile market conditions of the sample. As such, we define lagged returns using compounded S&P500 returns over the previous year. The momentum portfolios are then constructed for up-market and down-market sub samples.

'Front-Running' Momentum Portfolios

To date, research on the momentum effect has focused on portfolios formed at the end of the month. Our 'front-running' relative strength portfolios are constructed in a similar fashion to that of the regular, month-end momentum portfolios. The fundamental difference between these portfolios and the month-end portfolios is the portfolio evaluation date. Conventional month-end momentum strategies rank stocks on their prior return at the end of each month, such that portfolio positions can be entered at the start of the following month. In contrast, the 'front-running strategy' involves evaluating ranking returns a period of five business days before the end of the month. The portfolio positions are then entered into the next business day, five days before the start of the following month. The stocks are hence ranked on the following criteria:

$$R_{i\tau} = (1 + r_{\tau-J})(1 + r_{\tau-(J-1)})\ldots(1 + r_{\tau-1}) \tag{2}$$

where r_τ is the compounded daily return on stock i for the month ending five business days before the end of the month and J is the length of the ranking period in months. For example, during April 2004, a normal, month-end momentum portfolio using a 6/0/6 strategy ranks the universe of common stocks with at least six months of return data over the period of 31st October 2003 to the 30th April 2004, holding the resultant momentum portfolio from 1st May 2004 to the 29th October 2004. The corresponding 'front-running' momentum strategy would rank the universe of stocks that satisfy the above criteria on their performance over the period of 24th October 2003 to the 23rd April 2004, holding the resultant momentum portfolio from 26th April 2004 to the 22nd October 2004.

Size Subsamples

As prior research has found that the momentum effect is present in both small and large-cap subsamples, of interest is whether this has continued in the sample period. As noted by Jegadeesh and Titman (2001) the robustness of momentum to size subsamples would provide strong evidence that momentum strategies are actionable. If however, momentum returns are not present in a specific sub sample, this may indicate that institutional trading has eliminated momentum returns for those stocks. As liquidity risk and transaction costs may impede the usage of momentum strategies for smaller stocks, the presence of momentum returns in large stocks would provide stronger evidence of the momentum effect.

Size subsamples are also used to investigate whether the 'front-running' effect is greater for any sub sample of stocks as per our hypothesis. We sort stocks into three groups, small capitalization stocks, mid-capitalization stocks and large capitalization stocks with reference to the NYSE market capitalization deciles. At the portfolio evaluation date, firms with a market capitalization that would place it in the two lowest market capitalization deciles of listed NYSE stocks are classified as small stocks. Firms with a market capitalization above the median NYSE-listed stock are classified as large stocks, with the remainder classified as medium stocks. Alternatively, we could sort the stocks such that they contain a set proportion of the sample. However, as our sample includes NASDAQ and AMEX stocks, such a classification would result in the middle subsample consisting almost entirely of small capitalisation stocks as NASDAQ and AMEX stocks are generally small. Approximately 60% of the stock months in our sample are for stocks with market capitalisations that would place them in the two lowest NYSE deciles. The use of market capitalisation deciles thus results in more distinct subsamples.

Overlap of Month-End and 'Front-Running' Momentum Portfolios

To examine the effect of institutional momentum trading more explicitly, we obtain the 'front-running' and month-end momentum returns for those stocks common to both portfolios. As the sample of stocks included in the resulting 'front-running' and month-end strategies are identical, any difference in returns can be attributed solely to the return pattern of momentum stocks. As such, we are able to discern whether there is a distinct pattern of returns at the month-end for momentum stocks. If institutional momentum trading systematically influences month-end stock returns, we would expect that the 'front-running' strategies would generate larger returns than equivalent month-end strategies.

To investigate the stocks common to month-end and 'front-running' momentum strategies, we match each monthly 'front-running' winner or loser portfolio to the corresponding month-end winner or loser portfolio. Those stocks that are bought or sold by both strategies in a particular month are the 'overlapped' stocks. Consequently, the 'overlapped stocks' 'front-running' and month-end momentum portfolios consist of these overlapped stocks. The overlapped stocks month-end and 'front-running' momentum strategies are then constructed as before.

RESULTS

We find that 'front-running' a momentum strategy generates economically if not statistically significant returns in excess of a month-end strategy for small firms. The returns of a 'front-running' strategy are consistently less volatile than that of an equivalent month-end strategy. The 'front-running' effect is most pronounced when using a three-month ranking period. In unreported results, we find that the large firm momentum effect is quite sensitive to the specification of the sample and strategy. Our momentum returns are not significant in the whole sample period, due to the abnormal momentum returns period during and after the market crash. In the sample period, momentum is related to stock market movements, but not to movements in the economy as a whole.

Momentum in the Entire Period

Table 1 presents the average monthly returns from several price momentum strategies over the period of 1993 to 2004. We report results for the bottom decile portfolio (R1), the top decile portfolio (R10) and the returns of a winner minus loser portfolio. Across the entire sample period, past winners outperform past losers by roughly one percent a month, with substantial variation in the profitability of individual momentum strategies. To illustrate, a strategy that ranks stocks on prior three-month returns and holds the resulting portfolios for three months (i.e. a 3/0/3 strategy) earns 0.28% per month, while a 6/1/3 strategy earns 1.01% per month.

These returns generated by momentum strategies in our study are comparable with those of previous literature. For example, the oft-studied strategy that ranks stocks on the previous six month returns and subsequently holds the momentum portfolio for the following six months (i.e. a 6/0/6 strategy) returns an average of 1.01% per month. In comparison, Jegadeesh and Titman (1993) report a corresponding return of 0.95% per month over the 1965 to 1989 period, whilst Jegadeesh and Titman (2001) report a return of 1.39% per month over the 1990 to 1998 period. Table 1 thus suggests that price momentum is present in our sample.

In contrast to previous studies, we find that the returns generated by momentum strategies are not statistically different to zero, with a *t*-statistic of 1.35 for the 6/0/6 strategy. In comparison, Jegadeesh and Titman (1993) and Jegadeesh and Titman (2001) report *t*-statistics of 3.07 and 4.71 for the 6/0/6 strategy. The statistical insignificance of our results is despite the obvious economic significance of the returns reported, with zero-cost returns of up 1.01% a month. A closer examination of our results suggests that the lack of statistical significance may be attributed to the highly volatile momentum returns in our sample, with the standard deviation of momentum returns using a 6/0/6 strategy 9.01%. Other strategies have similar standard deviations. Figure 1 plots the monthly time-series of returns for the 6/0/6 strategy. From the figure, it is readily apparent that the momentum returns in the sample period are highly volatile, explaining the statistical insignificance.

The portfolios in Panel A of Table 1 are formed at the end of the ranking period. Because bid-ask bounce and other market microstructure effects are likely to attenuate the momentum effect, we examine and report in Table 1 Panel B the returns of corresponding strategies that contain a 'skip' period of one month between the end of the ranking and the start of the holding period. Previous research (for example, see Jegadeesh and Titman, 1993) and Rouwenhorst, 1998) has shown strategies that wait a period of one month before holding the momentum portfolio generate higher returns and are less volatile than strategies that do not skip a month. As such, the significance of these strategies would indicate that short-term microstructure effects and return reversals are contaminating the intermediate-term price continuation effect. We find that a 6/1/6 strategy generates an average return of 1.17% per month *(t*-statistic = 1.669) which is significant at the 10 percent level. The standard deviation of returns for this strategy is 8.43%. The results therefore suggest that although short-term effects attenuate momentum effects in our sample, they cannot explain the insignificance of momentum returns in the sample period.

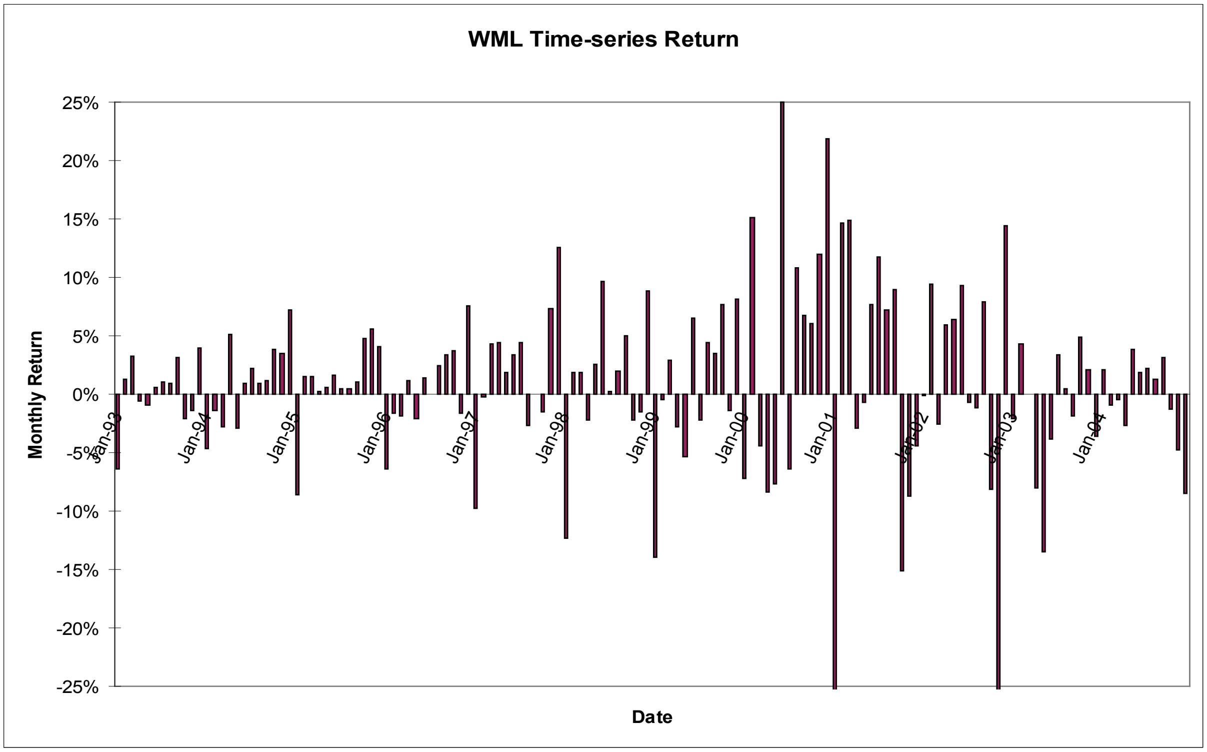
TABLE 1
MOMENTUM RETURNS WITH ONE MONTH SKIP PERIOD AND WITH IMMEDIATE PORTFOLIO FORMATION

Reported are the returns of the momentum portfolios based on *J*-month lagged returns and held for *K* months. The winner portfolio is an equally weighted portfolio of stocks in the highest lagged return decile. The loser portfolio is an equally weighted portfolio of stocks in the lowest return decile. The average monthly returns of these portfolios are presented along with the t-statistics in brackets. *, ** and *** denote significance at the 10, 5, and 1 % level.

Ranking Period		Holding Period (*K*)			
(J)	Portfolio	3	6	9	12
Panel A: No skip period					
3	Winner (R10)	1.378%	1.525%	1.438%	1.343%
		(2.12)**	(2.47)**	(2.41)**	(2.23)
	Loser (R1)	1.097%	0.825%	0.829%	0.848%
		(1.09)	(0.89)	(0.81)	(1.05)
	Winner - Loser	**0.281%**	**0.700%**	**0.610%**	**0.494%**
		(0.36)	(1.11)	(1.07)	(1.13)
6	Winner (R10)	1.887%	1.758%	1.609%	1.393%
		(2.83)**	(2.85)***	(2.61)**	(2.27)
	Loser (R1)	0.874%	0.748%	0.784%	0.892%
		(0.82)	(0.75)	(0.86)	(1.07)
	Winner - Loser	**1.013%**	**1.010%**	**0.824%**	**0.501%**
		(1.13)	(1.35)	(1.29)	(0.98)
Panel B: One month skip period					
3	Winner (R10)	1.433%	1.528%	1.440%	1.282%
		(2.24)**	(2.48)**	(2.41)**	(2.14)**
	Loser (R1)	0.584%	0.602%	0.680%	0.796%
		(0.62)	(0.68)	(0.81)	(1.04)
	Winner - Loser	**0.849%**	**0.925%**	**0.760%**	**0.487%**
		(1.24)	(1.56)	(1.53)	(1.27)
6	Winner (R10)	1.888%	1.765%	1.511%	1.286%
		(2.92)***	(2.85)***	(2.46)**	(2.11)**
	Loser (R1)	0.521%	0.592%	0.725%	0.874%
		(0.51)	(0.63)	(0.85)	(1.11)
	Winner - Loser	**1.368%**	**1.172%**	**0.785%**	**0.412%**
		(1.65)	(1.67)*	(1.42)	(0.91)

FIGURE 1
TIME SERIES OF MOMENTUM RETURNS

Figure 1 shows the time-series of one-month returns from a momentum strategy based on 6-month lagged returns, with no skip period and a holding period of 6 months (i.e. a 6/0/6 strategy).



Sub-Period Analyses

The results of the previous section indicate that while momentum strategies earn large returns during the sample period, these returns are not statistically distinguishable from zero for our sample period. This finding is in stark contrast to the bulk of the existing literature, with few prior studies documenting insignificant momentum profits in the US market. However, this result is not entirely unexpected, as our sample period is characterized by a bull market of abnormally large sustained stock market increases, followed by the market crash after September 2000. The strong stock market trends in the sample period are most pronounced amongst high-technology firms, which experienced unprecedented growth in the late 1990's and early 2000, a period commonly referred to as the 'tech-boom'. The subsequent crash in technology stocks beginning in March 2000 resulted in the NASDAQ declining almost 80% over the following eighteen months.

Portfolio Returns over 4-Year Sub Periods and in Different Market States

To investigate the effects of the tech crash on momentum returns, we examine momentum returns over four-year sub periods. Panel A of Table 2 reports the returns of the 6/1/6 strategy in each of three four-year sub periods in the 1993 to 2004 sample period. Our results indicate that momentum returns are positive and significant in the 1993 to 1996 and 1997 to 2000 periods. However, during the 2001 to 2004 period, momentum returns are negligible, with a winner minus loser portfolio returning 0.08% over this period. This indicates that the insignificant momentum result for the entire sample period is a result of the non-existent return subsequent to the tech crash.

TABLE 2
SUB-PERIOD RETURNS OF MOMENTUM PORTFOLIOS; 6/1/6 STRATEGY

Returns for momentum portfolios based on 6-month lagged returns, with a skip period of 1 month and a holding period of 6 months (i.e. a 6/1/6 strategy). Panel A reports the average momentum return within 4-year sub periods. The Equal Weighted Index is the returns on the equal-weighted index of all stocks over that period. The winner portfolio is an equally weighted portfolio of stocks in the highest lagged return decile. The loser portfolio is an equally weighted portfolio of stocks in the lowest return decile. Panel B reports momentum returns in different stock market states based on lagged 1-year S&P500 returns. On the left are results in up- and down-markets, and on the right are averages based on quartiles of lagged returns. The average monthly returns of these portfolios are presented along with the t-statistics in brackets. *, ** and *** denote significance at the 10, 5, and 1 % level.

Panel A: Subsamples by year

		Sub period		
Portfolio	1993-2004	1993-1996	1997-2000	2001-2004
Winner (R10)	1.758%	1.706%	1.756%	1.831%
	(2.85)***	(2.57)**	(1.18)	(2.02)**
Loser (R1)	0.748%	0.671%	-0.636%	1.756%
	(0.75)	(0.82)	-(0.43)	(0.77)
Winner - Loser	**1.010%**	**1.035%**	**2.393%**	**0.075%**
	(1.35)	(2.31)**	(2.21)**	(0.04)
Equal Weighted Index	1.697%	1.290%	0.684%	1.737%

Panel B: Subsamples by Aggregate Stock Market State

	Positive/Negative		Quartile			
Portfolio	$r_m<0$	$r_m>0$	Lowest	2	3	Highest
Winner (R10)	0.237%	2.298%	0.025%	1.330%	3.065%	2.666%
	(0.22)	(3.12) ***	(0.02)	(0.78)	(2.69)***	(3.35)***
Loser (R1)	-0.775%	1.069%	-1.057%	0.767%	1.205%	1.473%
	-(0.25)	(1.48)	-(0.34)	(0.55)	(1.10)	(1.17)
Winner - Loser	**1.012%**	**1.229%**	**1.082%**	**0.563%**	**1.860%**	**1.193%**
	(0.43)	(2.50)**	(0.45)	(0.55)	(3.26)***	(1.33)

To further investigate why momentum returns are not present in the 2001 to 2004 sub period and to examine the pattern of momentum returns, we classify each month in the sample period as either an up-market or down-market. Panel B of Table 2 reports the average return of a 6/1/6 strategy in each market state. Using this specification, the average momentum return in the 107 months defined to be an up-market is 1.23% per month, significant at the 5 percent level. Conversely, the average momentum return in the 37 months defined to be a down-market is a statistically insignificant 1.01% per month. This suggests that momentum returns are related to the performance of the market as a whole. As expected, the down-market periods are highly concentrated in the post-tech crash period, with the months between November 2000 and June 2003 accounting for 87% of the down-market observations.

In sum, our results indicate that the poor performance of momentum strategies during the sample period can be attributed to the negligible returns obtained during the 2001 to 2004 sub period. This in turn can be attributed to the poor contemporaneous performance of the stock market as a whole. As such, we show that momentum returns can be adversely affected by stock market-wide phenomena. The observed relationship between momentum returns and market states could be attributed to the wider macroeconomic environment. To address this concern, we use seasonally adjusted real GDP growth to sort our sample period into states of positive and negative GDP growth. Our results, not reported here for brevity, indicate that suggests that, for our sample, momentum returns are not related to GDP growth. Moreover, classifying months according to ex-post realised GDP growth is not useful to investors when making investment decisions.

Sub-Sample Analyses

Consistent with prior literature, the previous section has shown that momentum returns in the period 1993 to 2004 are linked to the performance of the stock market. Consistent with this relationship, momentum returns in the 2001 to 2004 sub period are negligible. As the stock market crash of 2000 was most pronounced in the smaller, high-tech firms, it is of interest whether the poor momentum return in the 2001 to 2004 sub period is confined to smaller or high-tech stocks.

Size Subsamples

As a robustness check, we examine the returns of momentum strategies restricted to stocks in specific market capitalization categories. Eliminating stocks in the two lowest NYSE market capitalization deciles results in a significant momentum return of 1.56% for the 6/1/6 strategy. Not only is this return less volatile than that of the full sample, but it is also substantially larger. We further sort firms by size, construct momentum portfolios for each size subsample, and find, consistent with Jegadeesh and Titman (1993), that momentum returns are somewhat related to firm size. Momentum returns are weaker for small stocks, with a marginally significant return of 1.15%; for the medium and large firms, momentum returns are significant and 1.70% and 1.46% respectively.

However, an analysis of the sub period results shows that the poor momentum return over the 2001 to 2004 sub period is not restricted to any size subsample. The large firm momentum strategy earns significant returns in only the 1997 to 2000 sub period. Moreover, although small and mid-size momentum strategies were profitable during the 1993 to 1996 and 1997 to 2000 sub periods, their returns over the 2001 to 2004 sub period are not significantly different from zero.

Exchange Subsamples

The inclusion of NASDAQ-listed stocks in the sample is rare in the momentum literature. To assess whether our results are due to the inclusion of NASDAQ-listed stocks in our sample, we examine the returns of a subsample including only stocks listed on the NYSE or AMEX, and one consisting entirely of stocks listed on NASDAQ.

Table 3 reports the returns of the 6/1/6 strategy for the two exchange-based sub samples. Consistent with the results for the size sorts, we find that momentum returns are larger for the NYSE/AMEX subsample, with the NYSE/AMEX subsample generating more significant returns for all sub periods. Over the entire period, a momentum strategy that selects stocks from the NYSE and AMEX returns a significant 1.18% per month, while a momentum strategy restricted to NASDAQ stocks returns an insignificant 1.08% per month. Pertinently, we find that within the NYSE/AMEX subsample momentum returns are significant for the entire sample period and highly significant for the 1993 to 1996 and 1997 to 2000 sub periods. In unreported results, the length of the holding period does not materially affect these results, with all but one strategy using a six-month ranking period significant over the sample period, and all highly significant over the 1993 to 2000 sub period. The results for the NYSE/AMEX subsample are thus more consistent with prior literature than the full sample results, for which only one of the 32 momentum strategies is (marginally) significant. We also find that the NYSE/AMEX momentum strategy has a substantially lower standard deviation of returns (6.00%) relative to the full sample (8.43%).

TABLE 3
EXCHANGE-SUB SAMPLE RETURNS OF MOMENTUM PORTFOLIOS

Reported are the returns for momentum portfolios based on 6-month lagged returns, with a skip period of 1 month and a holding period of 6 months (i.e. a 6/1/6 strategy). Panel A reports the average momentum return within a sample constructed using only NYSE and AMEX-listed stocks. Panel B reports the results from a sample of NASDAQ-listed stocks. The winner portfolio is an equally weighted portfolio of stocks in the highest lagged return decile. The loser portfolio is an equally weighted portfolio of stocks in the lowest return decile. The average monthly returns of these portfolios are presented along with the t-statistics in brackets. *, ** and *** denote significance at the 10, 5, and 1 % level.

Panel A: NYSE/AMEX Sub sample

		Sub period		
Portfolio	1993-2004	1993-1996	1997-2000	2001-2004
Winner (R10)	1.749%	2.070%	1.461%	1.718%
	(4.18)***	(3.62)***	(1.70)*	(2.35)**
Loser (R1)	0.571%	0.713%	-0.702%	1.715%
	(0.86)	(1.16)	-(0.70)	(1.07)
Winner - Loser	**1.179%**	**1.357%**	**2.163%**	**0.003%**
	(2.36)**	(3.74)***	(3.01)***	(0.00)

Panel B: NASDAQ Sub sample

		Sub period		
Portfolio	1993-2004	1993-1996	1997-2000	2001-2004
Winner (R10)	1.723%	1.508%	1.820%	1.842%
	(2.47)**	(2.12)**	(1.07)	(1.80)*
Loser (R1)	0.643%	0.776%	-0.679%	1.848%
	(0.62)	(0.86)	-(0.41)	(0.75)
Winner - Loser	**1.080%**	**0.732%**	**2.499%**	**-0.006%**
	(1.45)	(1.41)	(2.21)**	(0.00)

‘Front-Running’ Momentum Strategies

Across the entire sample, we find that our ‘front-running’ momentum strategy generates zero-cost portfolio returns of approximately one percent a month. As with the month-end strategies, there is substantial variation in the profitability of individual ‘front-running’ momentum strategies. Panel A of Table 4 presents the average monthly returns for the losers (R1), winners (R10) and the winner minus loser portfolio for strategies with a gap period of one month. The results are qualitatively similar for the same strategies without a gap period; we omit the tables for brevity.

In contrast to the month-end strategies, the returns of a number of the ‘front-running’ strategies are significant across the entire period. For example, the 6/1/3 strategy generates a significant positive return when a ‘front-running’ evaluation date is used, whereas the corresponding month-end strategy produces an insignificant return. In general, the momentum returns of ‘front-running’ strategies are broadly similar to, if not slightly greater than their equivalent month-end momentum strategies. In addition, the ‘front-running’ strategies are less volatile than the month-end strategies, with a lower standard deviation for all of the 32 strategies examined.

The uniformly lower standard deviation of the ‘front-running’ strategies is particularly interesting, as it indicates that using a ‘front-running’ portfolio evaluation date results in less volatile returns. This suggests that there is increased return volatility at the end of the month, consistent with institutional trading impacting on returns.

TABLE 4
RETURNS OF 'FRONT-RUNNING' MOMENTUM PORTFOLIOS; SIZE SUBSAMPLE

Panel A reports the average monthly returns for 'front-running' momentum portfolios based on *J*-month lagged returns, with a holding period of *K* and a 1-month gap between the ranking and holding periods. Panels B and C report the returns for strategies based on 3-month lagged returns, with a holding period of *K* months, for a subsample of large capitalization stocks. Panel B reports the average returns for strategies that use a month-end portfolio evaluation date for the large firm subsample; Panel C reports the corresponding returns for 'front-running' strategies. The winner portfolio is an equally weighted portfolio of stocks in the highest lagged return decile. The loser portfolio is an equally weighted portfolio of stocks in the lowest return decile. The t-statistics are in parentheses; *, ** and *** denote significance at the 10, 5, and 1 % level.

Panel A: 'front-running' portfolios, one month gap period

Ranking Period		Holding Period (K)			
(J)	Portfolio	3	6	9	12
3	Winner (R10)	1.511%	1.576%	1.497%	1.316%
		(2.29)**	(2.47)**	(2.42)**	(2.13)**
	Loser (R1)	0.587%	0.591%	0.687%	0.800%
		(0.64)	(0.68)	(0.83)	(1.05)
	Winner - Loser	**0.924%**	**0.985%**	**0.810%**	**0.515%**
		(1.49)	(1.83)	(1.84)	(1.53)
6	Winner (R10)	1.871%	1.786%	1.535%	1.309%
		(2.80)***	(2.79)***	(2.42)**	(2.08)**
	Loser (R1)	0.539%	0.625%	0.764%	0.917%
		(0.54)	(0.68)	(0.91)	(1.18)
	Winner - Loser	**1.332%**	**1.161%**	**0.771%**	**0.392%**
		(1.78)*	(1.88)*	(1.61)	(0.99)

Panel B: Month-end portfolios, 3 month holding period one month gap period; Large cap stocks

Holding period/Portfolio	3	6	9	12
Winner (R10)	0.910%	1.081%	1.111%	0.976%
	(1.37)	(1.69)*	(1.84)*	(1.63)
Loser (R1)	0.263%	0.250%	0.320%	0.481%
	(0.37)	(0.36)	(0.46)	(0.73)
Winner - Loser	**0.647%**	**0.831%**	**0.791%**	**0.495%**
	(0.99)	(1.46)	(1.59)	(1.18)

Panel C: 'front-running' portfolios, three month holding period, one month gap period; Large cap stocks

Holding period/Portfolio	3	6	9	12
Winner (R10)	0.952%	1.067%	1.099%	0.960%
	(1.47)	(1.70)*	(1.85)*	(1.63)
Loser (R1)	0.490%	0.389%	0.386%	0.530%
	(0.72)	(0.57)	(0.57)	(0.82)
Winner - Loser	**0.461%**	**0.677%**	**0.713%**	**0.430%**
	(0.80)	(1.29)	(1.55)	(1.09)

The returns of ‘front-running’ momentum strategies for the three month ranking period are higher than the corresponding month-end strategies for all investment horizons. The excess return of the ‘front-running’ momentum strategies over their month-end counterparts ranges from an annualized return of 0.34% to 2.77%. The magnitude of these differences suggests that using a ‘front-running’ strategy may generate economically significant returns in excess of a month-end strategy with lower volatility. The *t*-statistic of all such strategies are higher when using a ‘front-running’ strategy, and of the strategies that employ a three-month ranking period, the returns of two are statistically significant using a ‘front-running’ strategy. In contrast, none of the corresponding month-end strategies generated significant returns. Consistent with our hypothesis, the ‘front-running’ effect appears to be strongest in momentum strategies that use a three-month ranking period. Conversely, the returns of ‘front-running’ strategies that use 6, 9 or 12 month ranking criteria are virtually identical to the equivalent month-end strategy.

The Structure of ‘Front-Running’ Momentum Returns

It is possible that the insignificant differences of returns in ‘front-running’ strategies are caused by the returns of the ‘front-running’ portfolio being contaminated by stocks that are not affected by institutional momentum trading. If this is the case, restricting the sample to those stocks likely to experience momentum trading should lead to a more distinct ‘front-running’ effect. To this end, prior research has suggested that momentum trading is predominantly a winners phenomenon (Badrinath and Wahal, 2002), which is itself primarily a large firm phenomena (Grinblatt, Titman and Wermers, 1995). As such, one would expect that the ‘front-running’ effect would be greater amongst large cap winners.

We examine the returns of month-end and ‘front-running’ momentum strategies for a subsample of large stocks. As our results, consistent with prior studies, indicate that the ‘front-running’ effect is strongest when a three-month ranking period is used, we limit our analysis to a three-month ranking period. Panels B and C of Table 4 show that the ‘front-running’ effect is not more pronounced in large capitalization stocks nor can it be attributed to large capitalization winners. Rather, we find that ‘front-running’ strategies have lower returns, standard deviations and *t*-statistics amongst large capitalization stocks as compared to analogous month-end strategies

CONCLUSIONS

We find large variations in returns from momentum strategies. Momentum strategies did not earn significant returns during the period of 1993-2004, due to their particularly poor performance over the period from 2001-2004. A sample period specific finding is that returns of momentum portfolios restricted to NYSE and AMEX stocks are stronger than when NASDAQ stocks are included. We find that the previously documented large firm momentum effect is sensitive to the momentum strategy examined, and is in our sample driven by the abnormal returns of large NASDAQ stocks. Further we evaluate momentum strategies that do not adhere to the end of month portfolio formation universally used in the academic literature. We form portfolios one week prior to the end of month and call them ‘front-running’ momentum portfolios. Consistent with institutional momentum trading affecting end of month returns and volatility, we find that ‘front-running’ a momentum strategy generates economically significant returns in excess of a month-end strategy for small firms. Pertinently, the returns of a ‘front-running’ strategy are consistently less volatile than that of an equivalent month-end strategy.

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