# Momentum

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Abstract

There is substantial evidence that indicates that stocks that perform the best (worst) over a three to 12 month period tend to continue to perform well (poorly) over the subsequent three to 12 months. Momentum trading strategies that exploit this phenomenon have been consistently profitable in the United States and in most developed markets. Similarly, stocks with high earnings momentum outperform stocks with low earnings momentum. This article reviews the evidence of price and earnings momentum and the potential explanations for the momentum effect.

A growing body of literature documents evidence of stock return predictability based on a variety of firm-specific variables. Among these anomalies, the return momentum effect is probably the most difficult to explain within the context of the traditional risk-based asset pricing paradigm. For example, Jegadeesh and Titman (1993) show that stocks that perform the best (worst) over a three to 12 month period tend to continue to perform well (poorly) over the subsequent three to 12 months. The best performers appear to be no more risky than the worst performers. Therefore, standard risk adjustments tend to increase rather than decrease the return spread between past winners and past losers. Moreover, as we show in Figure 1, the returns of a zero cost portfolio that consists of a long position in past winners and a short position in past losers makes money in every five year period since 1940. It is difficult to develop a risk-based theory to explain cross-sectional differences in stock returns that are almost never negative.

Practitioners in the money management industry are aware of the momentum effect and it appears that they at least screen stocks based on price momentum. For example, Grinblatt, Titman and Wermers (1995) and Chan, Jegadeesh and Wermers (2000) find that mutual funds tend to buy past winners and sell past losers. Also, Womack (1996) reports that analysts generally recommend high momentum stocks more favorably than low momentum stocks. However, despite the popularity of momentum strategies in the investment community and its visibility in the academic community, there is no evidence of the effect disappearing. Jegadeesh and Titman (2001a) show that momentum strategies were profitable in the nineties as well, which is a period subsequent to the sample period in Jegadeesh and Titman (1993).

The momentum strategies are also profitable outside the United States. For example, Rouwenhorst (1998) reports that the momentum strategies examined by Jegadeesh and Titman (1993) for the U.S. market is also profitable in the European markets. Indeed, Japan is the only large developed stock market that does not exhibit momentum, (see, Chui, Titman and Wei (2000)). Momentum strategies implemented on samples consisting of stocks from a number of less developed stock markets also exhibit momentum, (see Rouwenhorst (1999) and Chui, Titman and Wei (2000)), although the momentum strategies within individual countries in their sample are often not profitable.

In addition, a recent paper by Chan, Hameed, and Tong (2000) provide evidence that international stock market indexes exhibit momentum.

This article presents a review of the evidence on momentum strategies. Section 1 provides a brief summary of the evidence on return momentum. Section 2 discusses the potential sources of momentum profits. Section 3 briefly describes some of the behavioral explanations for the momentum effect. These behavioral explanations have implications for the long horizon returns of momentum portfolios, as well as for cross-sectional difference in momentum profits. Section 4 and Section 5 review the empirical evidence in the context of these predictions. Section 6 summarizes the literature on earnings momentum and the relation between earnings and price momentum, and Section 7 provides our conclusions.

## 1. The Momentum Evidence

If stock prices either overreact or underreact to information, then profitable trading strategies that select stocks based on their past returns will exist. In an influential paper, DeBondt and Thaler (1985) examine the returns of contrarian strategies that buy past losers and sell past winners. Specifically, they consider strategies with formation periods (the period over which the past returns are measured) and holding periods of between one and five years and found that in most cases, contrarian portfolios earned significantly positive returns.[1] Jegadeesh (1990) and Lehmann (1990) examine the performance of trading strategies based on one week to one month returns and find that these short horizon strategies yield contrarian profits over the next one week to one month. These studies of very long-term and very short-term reversals generally led to the conclusion that stock prices overreact to information.

In contrast to these studies, Jegadeesh and Titman (JT) (1993) examine the performance of trading strategies with formation and holding periods between three and 12 months. Their strategy selects stocks on the basis of returns over the past J months and holds them for K months. This J-month/K-month strategy is constructed as follows: At the beginning of each month *t*, securities are ranked in ascending order on the basis of their returns in the past J months. Based on these rankings, JT form ten equally weighted decile portfolios. The portfolio with the highest return is called the “winners” decile and the portfolio with the lowest return is called the “losers” decile.

Jegadeesh and Titman (1993) examine U.S. stocks during the 1965 to 1989 period. Table I reports the average returns of the different buy and sell portfolios as well as the zero-cost, winners minus losers portfolio, for the strategies described above. All strategies considered here earn positive returns. The table also presents the returns for a second set of strategies that skip a week between the portfolio formation period and holding period. By skipping a week, these strategies avoid some of the bid-ask spread, price pressure, and lagged reaction effects that underlie the evidence documented in Jegadeesh (1990) and Lehmann (1990).

[1] A notable exception in their results was the contrarian portfolio with a one year formation period and a one year holding period, which earned negative returns. Since DeBondt and Thaler were focused on the longer-term contrarian strategies, they provide no further analysis of the momentum effect that was apparent over the one-year horizon.

All these returns are statistically significant except for the 3-month/3-month strategy that does not skip a week. The most successful zero-cost strategy selects stocks based on their returns over the previous 12 months and then holds the portfolio for 3 months.  This strategy yields 1.31% per month (see Panel A) when there is no time lag between the portfolio formation period and the holding period. The 6-month formation period produces returns of about 1 % per month regardless of the holding period.

**Evidence around the world**

Momentum strategies are profitable in many major markets throughout the world. Rouwenhorst (1998) replicates JT for 12 European countries and Table 2 presents his findings. The returns associated with these momentum strategies are very close to the return that JT report for the U.S., although the *t*-statistics are slightly larger for the European sample. For example, the six-month/six-month strategy with European stocks earns 1.16% (*t*-statistic = 4.02) compared with that of .95% (*t*-statistic = 3.07) for the U.S. market. Therefore, the profitability of momentum strategy appears to be a pervasive phenomenon.

**Seasonality**

Momentum strategies exhibit an interesting pattern of seasonality in January. Table 2 presents the returns for the six-month/six-month momentum strategy within and outside January, which is reproduced from Jegadeesh and Titman (2001a). This basic strategy in this paper is the same as that in JT although the samples are slightly different. Jegadeesh and Titman (2001a) covers the 1965 to 1998 sample period and it includes Nasdaq stocks while JT consider only NYSE and AMEX listed stocks. However, Jegadeesh and Titman (2001a) exclude stocks with low liquidity by screening out stocks priced less than $5 and stocks in the smallest market cap decile, based on NYSE size decile cut off.

The momentum strategy implemented on this sample earns a (negative) return of

-1.55% in January,[2] and positive returns in every calendar month outside of January. The average non-January return is 1.48% per month. Previous studies have also found a January seasonality for the size effect (see Keim, 1983) and for the long term return reversals. In contrast with these anomalies, however, the January seasonality hurts the momentum effect. Also, much of the size effect and long horizon return reversals are concentrated in January, while the momentum effect is entirely a non-January effect.

## 2. Potential Sources of Momentum Profits

A natural interpretation of momentum profits is that stocks underreact to information. For example, if a firm releases good news and stock prices only react partially to the good news, then buying the stocks after the initial release of the news will generate profits. However, this is not the only source of momentum profits. Momentum strategies can also be profitable if past winners happen to be riskier than past losers. Also, if the premium for bearing certain types of risk varies across time in a serially correlated fashion, momentum strategies will be profitable. To formalize these ideas, consider the following single factor model:[3]

$$\begin{aligned} r_{it} &= m_i + b_i f_t + e_{it}, \\ E(f_t) &= 0 \\ E(e_{it}) &= 0 \\ Cov(e_{it}, f_t) &= 0, \quad \forall i \\ Cov(e_{it}, e_{jt-1}) &= 0, \quad \forall i \neq j \end{aligned} \qquad (1)$$

where $\mu_i$ is the unconditional expected return on security $i$, $r_{it}$ is the return on security $i$, $f_t$ is the unconditional unexpected return on a factor-mimicking portfolio, $e_{it}$ is the firm-specific component of return at time $t$, and $b_i$ is the factor sensitivity of security $i$.

The superior performance of the momentum strategies implies that stocks that generate higher than average returns in one period also generate higher than average returns in the period that follows. In other words, these results imply that:

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[2] JT report that the momentum strategy earns -6.86% in January. The negative return in Jegadeesh and Titman (2001) is smaller because they exclude the smallest firms, which account for much of the January return reversals.

[3] The model we discuss here is from JT. Similar models have also been used by Lo and MacKinlay (1990) and Jegadeesh (1990) to understand the sources of short horizon contrarian profits.

$$E(r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1} > 0) > 0$$

and

$$E(r_{it} - \bar{r}_t | r_{it-1} - \bar{r}_{t-1} < 0) < 0,$$

where a bar above a variable denotes its cross-sectional average.

Therefore,

$$E\{(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})\} > 0. \tag{2}$$

The above cross-sectional covariance turns out to equal the expected profits to a trading strategy, considered in Lehmann (1990) and Lo and MacKinlay (1990), that weights stocks by the difference between their past returns and the past returns of the equally weighted index. This weighted relative strength strategy (WRSS) is closely related to the strategy in Table 1 and it has a correlation of .95 with the returns on P10-P1. While the equally weighted decile portfolios are used in most empirical tests, the closely related WRSS provides a tractable framework for analytically examining the sources of momentum profits and evaluating the relative importance of each of these sources.

Given the one-factor model defined in (1), the WRSS profits given in Equation (2) can be decomposed into the following three terms:

$$E\{(r_{it} - \bar{r}_t)(r_{it-1} - \bar{r}_{t-1})\} = s_m^2 + s_b^2 Cov(f_t, f_{t-1})$$

$$+ Cov_i(e_{it}, e_{it-1}), \tag{3}$$

where $s_\mu^2$ *and* $s_b^2$ are the cross-sectional variances of expected returns and factor sensitivities respectively.

This decomposition suggests three potential sources of momentum profits. The first term in this expression is the cross-sectional dispersion in expected returns. Intuitively, since realized returns contain a component related to expected returns, securities that experience relatively high returns in one period can be expected to have higher than average returns in the following period. The second term is related to the potential to time the factor. If factor portfolio returns are positively serially correlated, large factor realizations in one period will be followed by higher than average factor realizations in the next period. The momentum strategy tends to pick stocks with high b's following periods of large factor realizations, and hence it will benefit from the higher expected future factor realizations. The last term in the above expression is the average serial covariance of the idiosyncratic components of security returns.

To assess whether the existence of momentum profits imply market inefficiency, it is important to identify the sources of the profits. If the profits are due to either the first or the second term in Equation (3), they may be attributed to compensation for bearing systematic risk and need not be an indication of market inefficiency. However, if the superior performance of the relative strength strategies is due to the third term, then the results would suggest market inefficiency.

**Cross-sectional differences in expected returns**

We can examine whether cross-sectional differences in risk explain momentum profits by examining risk adjusted returns under specific asset pricing models. JT adjust for risk using the CAPM benchmark, and Fama and French (1996), Grundy and Martin (2001) and Jegadeesh and Titman (2001a) adjust for risk using the Fama-French three-factor model benchmark.

First, consider the characteristics of the momentum portfolios. Table 3 presents the size decile ranks based on NYSE size decile cutoffs with the size rank of 1 being the smallest and the size rank of 10 being the largest. Both winners and losers tend to be smaller firms than the average stock in the sample because smaller firms have more volatile returns and are thus more likely to be in the extreme return sorted portfolios. The average size rank for the winner portfolio is larger than that for the loser portfolio.

Table 3 also presents the sensitivities of these portfolios to the three Fama-French factors. The results indicate that the market betas for winners and losers are virtually the same. However, the losers are somewhat more sensitive to the size factor than are the winners (the factor sensitivity for the losers is .55 compared to .41 for the winners). Moreover, the winners have a loading of -.245 on the HML factor while the losers have a loading of -.02.

The relative sensitivities of the extreme portfolios to the SMB and HML factors reflect the natural relation between past returns, and firm size and book-to-market ratios. The winners increase in market capitalization over the ranking period and hence tend to be larger firms and have lower book-to-market ratios than the losers. Therefore, the SMB and HML sensitivities of losers are larger than that for the winners. Overall, the results in Table 3 indicate that the losers are riskier than the winners since they are more sensitive to all three Fama-French factors.

Table 4 reports the alphas of the various momentum portfolios estimated by regressing the monthly momentum returns (less the risk free rate except for the zero investment P1-P10 portfolio) on the monthly returns of both the value-weighted index less the risk free rate and the three Fama-French factors. The CAPM alpha for the winner minus loser portfolio is about the same as the raw return difference since both winners and losers have about the same betas. The Fama-French alpha for this portfolio is 1.36%, which is larger than the corresponding raw return of 1.23% reported by Jegadeesh and Titman (2001a). This difference arises because the losers are more sensitive to the Fama-French factors.

The above evidence indicates that the cross-sectional differences in expected returns under the CAPM and the Fama-French three-factor model cannot account for the momentum profits. However, it is possible that these models omit some priced factors and hence provide inadequate adjustments for differences in risk. Conrad and Kaul (1998) use the sample mean of realized return of each stock as their measure of the stock's expected return and circumvent the need for specifying an equilibrium asset pricing model. They directly use the decomposition in Equation (3) to examine the contribution of cross-sectional differences in expected returns (the first term on the right hand side) to momentum profits. They find that the cross-sectional variance of sample mean returns is close to the momentum profits for the WRSS. This finding leads them to conclude that the observed momentum profits can be entirely explained by cross-sectional differences in expected returns rather than any ``time-series patterns in stock returns."

Jegadeesh and Titman (2001b), however, point out that while sample mean is an unbiased estimate of unconditional expected return, the cross-sectional variance of sample mean is not an unbiased estimate of the variance of true expected returns. Since sample means contain both the expected and unexpected components of returns, variance of sample mean is the sum of the variances of these components. Consequently, the variance of sample mean overstates the dispersion in true expected returns. Jegadeesh and Titman (2001b) present tests that avoid this bias and find that very little, if any, of the momentum profits can be attributed to cross-sectional differences in expected returns.

**Serial covariance of factor returns**

JT examine whether the serial covariance of factor returns, the second term in the decomposition given by Equation (3), can explain momentum profits. Under model (1), the serial covariance of an equally weighted portfolio of a large number of stocks is:[4]

$$\mathrm{cov}(\bar{r}_t, \bar{r}_{t-1}) = \bar{b}_i^2 \mathrm{Cov}(f_t, f_{t-1}). \tag{4}$$

If the serial covariance of factor related returns were to contribute to momentum profits, then the factor realizations should be positively serially correlated (see Equation (3)). Although the underlying factor is unobservable, Equation (4) indicates that the serial covariance of the equally weighted market index will have the same sign as that of the common factor. JT examine this implication and find that the serial covariance of 6-month returns of the equally weighted index is negative (-0.0028). Since the momentum strategy can only benefit from positive serial covariance in factor returns, the finding here indicates that the negative factor return serial covariance does not contribute to momentum profits.

**Lead-lag effects and momentum profits**

Momentum profits can also potentially arise if stock prices react to common factors with some delay. Intuitively, if stock prices react with a delay to common information, investors will be able to anticipate future price movements based on current factor realizations and devise profitable trading strategies. In some situations such delayed reactions will result in profitable contrarian strategies and in some other

[4] The contribution of the serial covariances of $e_{it}$ to the serial covariance of the equally weighted index becomes arbitrarily small as the number of stocks in the index becomes arbitrarily large.

situations, it will result in profitable momentum strategies. To see this, consider the following return generating process:

$$r_{it} = \mu_i + ß_{0i} f_t + ß_{1i} f_{t-1} + e_{it}, \tag{5}$$

where $ß_{0i}$ and $ß_{1i}$ are sensitivities to the contemporaneous and lagged factor realizations. $ß_{1i} > 0$ implies that stock $i$ partly reacts to the factor with a lag, and $ß_{1i} < 0$ implies that the stock overreacts to contemporaneous factor realizations and this overreaction gets corrected in the subsequent period.

This type of delayed reaction model has been used to characterize stock return dynamics in Lo and MacKinlay (1990), JT, Jegadeesh and Titman (1995) and Brennan, Jegadeesh and Swaminathan (1993) among others. This model captures the empirical finding that stock returns are sensitive to lagged market returns (see Jegadeesh and Titman (1995)).

The WRSS profits under this model is given by:

$$E\{(r_{it} - r_t)(r_{it-1} - \bar{r}_{t-1})\} = s_{\mu}^{2} + d\, s_{f}^{2}. \tag{6}$$

where,

$$d = \frac{1}{N} \sum_{i=1}^{N} (ß_{0i} - \bar{b}_0)(ß_{1i} - \bar{b}_1),$$

and, $\bar{b}_0$ and $\bar{b}_1$ are the cross-sectional averages of $ß_0$ and $ß_{1i}$, *respectively*.

Equation (6) indicates that the delayed reaction will generate positive momentum profits when $d > 0$. Intuitively, $d$ is greater than zero if firms with large contemporaneous betas also tend to exhibit large lagged betas. Here, the contemporaneous betas are less dispersed than the sum of contemporaneous and lagged betas. When $d > 0$, stock prices tend to move together too closely with one another. In other words, if the market moves up, high beta stocks will increase more than low beta stocks, but not by as much as they should. Hence, the higher beta stocks will also react with a delay. It is possible that delayed reactions of this nature may be due to the tendency of investors to buy and sell stocks in baskets rather than individually. With such delayed reactions, a momentum strategy will buy high beta stocks following a market increase, and will profit from the delayed response in the following period.

When lead-lag effects are generated in this way, large factor realizations will be followed by large delayed reactions, and hence the profit in any period will depend on the magnitude of factor realizations in the previous period. Formally, consider the expected WRSS profits conditional on the past factor portfolio return:

$$E\{(r_{it} - \bar{r}_t)\,(r_{it-1} - \bar{r}_{t-1})|f_{t-1}\} = s_{\mu}^{2} + \mathrm{d}f_{t-1}^{2}. \tag{8}$$

Equation (8) implies that if the lead-lag effect contributes to momentum profits then the magnitude of the profits should be positively related to the squared factor portfolio return in the previous period.

To investigate the importance of this source JT estimate the following regression using the value-weighted index as a proxy for the factor portfolio:

$$\mathrm{r}_{pt,6} = a_i + ?r^{2}_{mt,-6} + u_{it},$$

where $r_{pt,6}$ is the WRSS profits and $\mathrm{r}_{mt,-6}$ is the demeaned return on the value-weighted index in the months $t$ – 6 through $t$ – 1. Their estimates of ? and the corresponding autocorrelation-consistent $t$-statistic over the 1965 to 1989 sample period are –1.77 and –3.56, respectively. The negative coefficients indicate that any marketwide lead-lag effect does not add to the momentum profits.

**Industry momentum**

The results discussed in the last section clearly indicate that the common factor in a single factor model cannot explain momentum profits. JT therefore conclude that the momentum profits are due to the non-market component of returns. While the non-market component is the idiosyncratic component of returns in a single factor model, it is possible that momentum is related to other factors in a more general multifactor setting. For example, if we introduce industry factors, serial covariance in industry returns, rather than the serial covariance of firm-specific component of returns may account for the momentum profits.

Moskowitz and Grinblatt (1999) evaluate momentum in industry returns. They form value-weighted industry portfolios and rank stocks based on past industry returns. They find that high momentum industries outperform low momentum industries in the six-months after portfolio formation. To assess the extent to which the industry return contributes to momentum profits, they examine the performance of a ``random industry" strategy. Specifically, they replace each firm in the winner and loser industries with other firms that are not in these industries, but have the same ranking period returns as the firms that they replace. The random industry portfolios have similar levels of past returns as the winner and loser industry portfolio. However, Moskowitz and Grinblatt find that the profit for the momentum strategy with the random industry earns close to zero returns. Based on this test they conclude that the momentum strategy profits from industry momentum and not from momentum in the firm specific component of returns.

Grundy and Martin (2001) reexamine the extent to which industry momentum contributes to momentum profits. Grundy and Martin replicate Moskowitz and Grinblatt and find that for a six-month ranking period and a contiguous six-month holding period, the actual industry strategy earns a significantly positive return of .78% while the simulated industry strategy earns zero returns (see Table 3, Panel A). Additionally, Grundy and Martin consider a strategy that skips a month between the ranking period and holding period in order to avoid the potential biases due to bid-ask spreads. When industry portfolios are formed in this manner, a momentum strategy does not yield significant profits either for the actual industry strategy or for the simulated industry strategy. In comparison, the momentum strategy with individual stocks earns a significantly positive profit of .79% during the 1966 to 1995 period.

Recall from Table 1 that the momentum strategy with individual stocks is more profitable when the ranking period and holding period are not contiguous than when they are contiguous. When the holding period and the ranking period are contiguous, the profits to the momentum strategy are attenuated by the negative serial correlation in returns induced by the bid-ask spreads, and by the short horizon return reversals.

In the case of industry momentum however, the profits entirely disappear for the six-month ranking period when the ranking period and the holding period are not contiguous. The industry momentum seems to benefit from the positive first order serial correlation while the individual stock momentum is reduced by short horizon return reversals.

A recent paper by Lewellyn (2001) also finds that industry portfolios generate significant momentum profits. Lewellyn, however, concludes that industry momentum is driven primarily by the lead-lag effect discussed above. Specifically, his evidence suggests that industry portfolio returns tend to move too much together.

## 3. Behavioral Models

As we mentioned in the introduction, it is very difficult to explain the observed momentum profits with a risk-based model. Therefore, researchers have turned to behavioral models to explain this phenomenon. Since these models are described in greater detail elsewhere in this book, we will provide only a brief description of the models in order to motivate some of the more recent empirical work on momentum.

Most of the models assume that the momentum-effect is caused by the serial correlation of individual stock returns, which as we discussed above, appears to be consistent with the evidence. However, they differ as to whether the serial correlation is caused by under-reaction or delayed overreaction. If the serial correlation is caused by underreaction, then we expect to see the positive abnormal returns during the holding period followed by normal returns in the subsequent period. However, if the abnormal returns are caused by delayed overreaction, then we expect that the abnormal momentum returns in the holding period will be followed by negative returns since the delayed overreaction must be subsequently reversed. Hence, these behavioral models motivate tests of the long-term profitability of momentum strategies that we will discuss below. In addition, the models have implications about the cross-sectional determinants of momentum, which are also discussed below.

Delong, Shleifer, Summers and Waldman (1990) were among the first economists to formally model how irrational portfolio strategies could affect asset prices. In particular, they show that "positive feedback trading strategies" (investment strategies that buy past winners and sell past losers) cause market prices to deviate from fundamental values. To a large extent, the subsequent literature presents behavioral models that formalize how various behavioral biases can lead investors to follow positive feedback strategies.

Barberis, Shleifer and Vishny (1998) discuss how a “conservatism bias” might lead investors to underreact to information, giving rise to momentum profits. The conservatism bias, identified in experiments by Edwards (1968), suggests that investors tend to underweight new information when they update their priors. If investors act in this way, prices will slowly adjust to information, but once the information is fully incorporated in prices there is no further predictability about stock returns.

Additionally, Barberis, et. al. hypothesize that investors identify patterns based on what Tversky and Kahneman (1974) refer to as a “representative heuristic.” Representative heuristic is the tendency of individuals to identify “an uncertain event, or a sample, by the degree to which it is similar to the parent population.” In the context of stock prices, Barberis et al. argue that the representative heuristic may lead investors to mistakenly conclude that firms realizing consistent extraordinary earnings growths will continue to experience similar extraordinary growth in the future. They argue that although the conservatism bias in isolation leads to underreaction, this behavioral tendency in conjunction with the representative heuristic can lead to prices overshooting their fundamental value and eventually, long horizon negative returns for stocks with consistently high returns in the past.[5]

Daniel, Hirshleifer and Subramanyam (1998) and Hong and Stein (1999) propose alternative models that are also consistent with short-term momentum and long-term reversals. Daniel, et al. argue that the behavior of informed traders can be characterized by a “self-attribution” bias. In their model, investors observe positive signals about a set of stocks, some of which perform well after the signal is received. Because of their cognitive biases, the informed traders attribute the performance of ex-post winners to their stock selection skills and that of the ex-post losers to bad luck. As a result, these investors become overconfident about their ability to pick winners and thereby

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[5] The time horizon over which various biases come into play in the Barberis, et al. (and in other behavioral models) is unspecified. One could argue that the six-month ranking period used in this paper may not be long enough for delayed overreaction due to the representative heuristic effect. In such an event we would only observe underreaction due to the conservatism bias.

overestimate the precision of their signals for these stocks. Based on their increased confidence in their signals, they push up the prices of the winners above their fundamental values. The delayed overreaction in this model leads to momentum profits that are eventually reversed as prices revert to their fundamentals.

Hong and Stein (1999) do not directly appeal to any behavioral biases on the part of investors but they consider two groups of investors who trade based on different sets of information. The informed investors or the “news watchers” in their model obtain signals about future cash flows but ignore information in the past history of prices. The other investors in their model trade based on a limited history of prices and, in addition, do not observe fundamental information. The information obtained by the informed investors is transmitted with a delay and hence is only partially incorporated in the prices when first revealed to the market. This part of the model contributes to underreaction, resulting in momentum profits. The technical traders extrapolate based on past prices and tend to push prices of past winners above their fundamental values. Return reversals obtain when prices eventually revert to their fundamentals. Both groups of investors in this model act rationally in updating their expectations conditional on their information sets but return predictability obtains due to the fact that each group uses only partial information in updating their expectations.

## 4. Long Horizon Returns of Momentum Portfolios

As we discussed earlier, the momentum-effect is consistent with both investors underreacting to information, as well as with investors overreacting to past information with a delay, perhaps due to positive feedback trading. The positive feedback effect, which is consistent with some of the behavioral models described in Section 3, implies that the momentum portfolio should generate negative returns in the periods following the holding periods considered in previous sections.

JT and Jegadeesh and Titman (2001a) examine the long horizon performance of momentum strategies to examine whether the evidence suggests returns reversals in the post-holding periods. Figure 3, which is reproduced from Jegadeesh and Titman (2001a), presents cumulative momentum profits over a 60-month post formation period. Over the 1965 to 1998 sample period, the results reveal a dramatic reversal of returns in the second through fifth years. Cumulative momentum profit increases monotonically until it reaches 12.17% at the end of Month 12. From Month 13 to Month 60 the momentum profits are on average negative. By the end of Month 60 the cumulative momentum profit declines to -.44%.

As Table 3 reports, the loser portfolios have larger sensitivities to the Fama and French size and book-to-market factors. The negative returns in the post-holding period may therefore represent compensation for factor risks. Panel C of Table 5 presents the Fama-French three-factor alphas for the zero cost momentum portfolio and separately for the winners and losers portfolios. The table reveals that the alpha of the zero cost momentum portfolio is approximately half the size of the raw returns in Month 13 to Month 60. The alphas are significantly negative only in years 4 and 5.

The robustness of long horizon return reversals can be evaluated by examining the performance of momentum portfolios in two separate time periods, the 1965 to 1981 and 1982 to 1998 sub periods. In addition to being the halfway point, 1981 represents somewhat of a break point for the Fama and French factor returns. The Fama-French SMB and HML factors have higher returns in the pre-1981 period (the monthly returns of the SMB and HML factors average .53% and .48% respectively) than in the post-1981 period (the monthly returns of the SMB and HML factors average -.18% and .33% respectively).

The evidence indicates that the momentum strategy is significantly profitable, and quite similar in both sub periods, in the first 12 months following the formation date. The returns in the post-holding periods, however, are quite different in the two sub periods. In the 1965 to 1981 subperiod, the cumulative momentum profit declines from 12.10% at the end of Month 12 to 5.25% at the end of Month 36 and then declines further to –6.29% at the end of Month 60. Hence, the evidence in this subperiod supports the behavioral models that suggest that positive feedback traders generate momentum. In the 1982 to 1998 subperiod the cumulative profit decreases insignificantly from 12.24%, at the end of month 12, to 6.68% at the end of Month 36 and then stays at about the same level for the next 24 months. Hence, the evidence in the second subperiod does not support the behavioral models.

## 5. Cross-Sectional Determinants of Momentum

The insights provided by the behavioral models also suggest that stocks with different characteristics should exhibit different degrees of momentum. For example, since the momentum-effect is due to inefficient stock price reaction to firm specific information, it is likely to be related to various proxies for the quality and type of information that is generated about the firm; the relative amounts of information disclosed publicly and being generated privately; and to the cost associated with arbitraging away the momentum profits.

The empirical evidence suggests that each of these factors is important. For example, JT and a number of more recent papers find that there is greater momentum for smaller firms. A recent working paper by Lesmond, Schill and Zhou (2001) reports that the most important cross-sectional predictor of the momentum-effect is the price level of the stock. Both firm size and price levels are correlated with transaction costs. Hence, the evidence in these papers suggests that differences in the momentum-effect across stocks is likely to be at least partly due to differences in transaction costs.

Hong, Lim and Stein (1998) find that even after controlling for size, firms that are followed by fewer stock analysts exhibit greater momentum. Table 7, which reprints a table in Hong, Lim and Stein (1998), shows that the returns associated with a momentum strategy implemented on stocks with relatively low analyst coverage are extremely strong.

This finding is consistent with the Hong and Stein (1999) prediction that slow dissemination of public information increases momentum profits. Since there is less public information about stocks with low analyst coverage, information about the companies may be incorporated into their stock prices more slowly. In addition, given that there is less public information available about these stocks, one might expect relatively more private information to be produced, which Daniel, Hirshleifer and Subrahmanyam (1998) suggests will increase price momentum.

Daniel and Titman (1999) find that momentum profits are significantly higher when the strategy is implemented on growth (low book-to-market) stocks rather than value (high book-to-market) stocks. Table 8, which reprints a table from Daniel and Titman, shows that the momentum profits are not reliably different from zero when implemented on stocks with the highest book-to-market ratios. They suggest that this result may be due to the fact that it is harder to evaluate growth stocks than to evaluate value stocks. Psychologists report that individuals tend to be more overconfident about their ability to do more ambiguous tasks. So, the overconfidence hypothesis suggests that momentum is likely to be greater for growth stocks.

Lee and Swaminathan (2000) examine the relation between momentum profits and turnover, and find that momentum is higher for stocks with greater turnover. Table 9, which presents results from their paper, shows that momentum profits are almost three times as high when implemented on stocks with the highest turnover rather than stocks with the lowest turnovers. This finding is somewhat surprising when viewed from the transaction cost perspective. Stocks with higher turnover can be traded more easily, and generally, there is more public information generated for high turnover stocks than for low turnover stocks.

One potential explanation for their findings may be that there are larger differences in opinion about higher turnover, and larger differences of opinion may arise from difficulties in evaluating the fundamental values of these stocks. Hence, the Daniel and Titman explanation for why growth stocks exhibit greater momentum may also apply to high turnover stocks. Another explanation is that turnover is related to the amount of attention that a stock attracts. Hence, high turnover stocks may be more exposed to positive feedback trading strategies proposed by Delong, Shleifer, Summers and Waldman (1990).

## 6. Earnings Momentum

The results so far have focused on the profitability of momentum strategies based on past returns. Naturally, returns are driven by changes in underlying fundamentals. Stock returns tend to be high, for example, when earnings growth exceeds expectations or when consensus forecasts of future earnings are revised upward. An extensive literature examines return predictability based on momentum in past earnings and momentum in expectations of future earnings as proxied by revisions in analyst forecasts. This section reviews the evidence from the earnings momentum literature and presents the interaction between earnings momentum and return momentum.

A partial list of papers that investigate the relation between past earnings momentum and futures returns are Jones and Litzenberger (1970), Latane and Jones (1979), Foster, Olsen and Shevlin (1984), Bernard and Thomas (1989), and Chan, Jegadeesh and Lakonishok (1996). These papers typically measure earnings momentum using a measure of standardized unexpected earnings (SUE). SUE is defined as:

$$SUE = \frac{\text{Quarterly earnings} - \text{Expected quarterly earnings}}{\text{Standard deviation of quarterly earnings}}.$$

These papers use variations of time series models to determine earnings expectations. Typically, the papers assume that quarterly earnings follow a seasonal random walk with drift. However, these papers differ to some extent in their specification of the growth in same fiscal quarter earnings. Specifically, Jones and Litzenberger (1976) and Latane and Jones (1979) assume that quarterly earnings grow at a constant rate, Foster, et al. (1984) and Bernard and Thomas (1989) model quarterly earnings growth as an AR(1) process and Chan, et al. (1996) assume zero growth in quarterly earnings.

Among these statistical models for quarterly earnings growth, the AR(1) model is the most realistic specification since it captures the mean reversion in earnings growth.[6] However, the robustness of the results in the literature indicates that the accuracy of the earnings expectation model is not particularly important for the purposes of measuring unexpected earnings to predict returns.

Table 10 summarizes the results from returns on portfolios formed based on SUE. Latane and Jones examine the profitability of SUE strategies over the 1974-77 sample period and find that the difference in returns between the extreme SUE portfolios is about 7.3% over a six month period. The extreme portfolios in Latane and Jones comprise stocks with SUE greater than 2 for the high SUE portfolio and less than -2 for the low SUE portfolio. With this definition of high and low SUE, roughly 15% of the stocks in the sample are allocated to each extreme portfolio. Bernard and Thomas (1989) report similar levels of return differences across the extreme SUE deciles for the small and medium firms. For the large firms, the return difference across extreme decile portfolios is 4.1%.

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[6] See Foster, et al. (1984) for an evaluation of the relative accuracy of various statistical models to capture the time-series properties of quarterly earnings.

Chan, et al. (1996) find a six-month return difference of 7.5% across the extreme SUE portfolios over the 1973 to 1993 sample period. The return difference over a 12-month holding period is 7.5%, which is only marginally higher that the return difference for the first six months. Therefore, compared with the return momentum strategy the superior performance of the *SUE*-based strategy is relatively short-lived.

The partial review of the literature on the revision of analyst earnings forecasts is summarized in Table 11. A study by Givoly and Lakonishok (1979), which examines a sample of 67 firms from 1967 to 1974, considers earnings forecast data from Standard and Poors Earnings forecaster. They form Up and Down revision portfolios that comprise stocks where the earnings forecast is revised upward or downward by 5% and find that the Up revision portfolio earns about 3.1% higher returns than the down portfolio. A more recent paper by Stickel (1991), which examines a sample of New York and American stock exchanges firms that are included in the Zacks Investment Research database over the 1981 to 1984 sample period, considers various measures of Up and Down revisions based on individual analyst forecast as well as consensus earnings forecast revisions. Stickel's Up and Down revision portfolios comprise 5% of stocks with the highest and lowest forecast revisions respectively. He finds that the Up revision portfolios earn 7.07% higher returns than the Down revision portfolios based on consensus forecast revisions and 6.36% higher returns based on individual analyst forecasts.

Chan, Jegadeesh and Lakonishok (1996) use the sample of firms covered by IBES over the 1977 to 1993 sample period. They define forecast revision as a six-month moving average of the ratio of consensus earnings forecast revision to the stock price. The Up and Down revision portfolios in Chan, et al. comprise the decile of stocks with the largest and smallest forecast revisions, respectively. Chan, et al. find that the Up revision portfolios earn 7.7% higher return than the Down revision portfolios over the six months after portfolio formation. The return difference is 8.7% 12 months after portfolio formation. Similar to the SUE based strategy, the profitability of analyst forecast revision strategy is also relatively short lived.

The collective evidence in the literature indicates that the analyst forecast revision strategy is remarkably robust. The profitability of this strategy is not sensitive to the specific definition of forecast revisions nor is it sensitive to the source of analyst forecasts. Also, both the SUE strategy and the forecast revision strategy have persisted for a fairly long period of time after the initial publication of the evidence.

**Relation between earnings and return momentum strategies**

Chan, et al. (1996) present a detailed analysis of the interactions among various momentum strategies and this subsection closely follows that paper. As Chan, et al. point out, it is possible that a price momentum strategy is profitable mainly because price momentum and earnings momentum are correlated, and earnings momentum may be the dominant source of return predictability. Alternatively, strategies based on price momentum and earnings momentum may be profitable because they exploit market underreaction to different pieces of information. For instance, earnings momentum strategies may exploit underreaction to information about the short-term prospects of companies that will ultimately be manifested in near-term earnings. Price momentum strategies may exploit slow reaction to a broader set of value-relevant information, including the long-term prospects of companies that have not been fully captured by near-term earnings forecasts or past earnings growth. If both these explanations were true, then a strategy based on past returns and on earnings momentum in combination should lead to higher profits than either strategy individually.

Chan, et al. (1996) present the correlation between price and earnings momentum variables and their results are reproduced in Table 12. Not surprisingly, the price momentum and earnings momentum measures are positively correlated with one another. The highest correlation (0.440) obtains for the two earnings momentum variables. The correlations of past six-month returns with standardized unexpected earnings and with analysts' forecast revisions indicate that past earnings surprises and revisions of expectations about the following year's earnings are about equal. The low correlations suggest, however, that the different momentum variables do not reflect the same information. Rather, they capture different aspects of improvement or deterioration in a company's performance.

**Two-Way Analysis**

Earnings and return momentum strategies are individually useful for predicting stock returns six to 12 months in the future. Because these variables tend to move together, it is possible that the findings may reflect not three separate effects but different manifestations of a single effect. For example, if earnings momentum, as reflected by SUE, is the direct source of return predictability, then it should subsume the predictive ability of the other variables. However, if each of these momentum variables contains different pieces of information about future returns then each variable should exhibit incremental predictive ability.

Chan, et al. (1996, 2000) address this issue with predictability tests based on two-way classifications. At the beginning of each month, they sort the stocks in their sample on the basis of their past six-month returns and assign them to one of three equal-sized portfolios. Independently, they sort stocks into three equal-sized portfolios on the basis of SUE and analyst forecast revisions. Each stock, therefore, falls into one of nine portfolios for each two-way sort.

Panel A of Table 13 reports the results when portfolios are based on rankings by past six-month returns and standardized unexpected earnings. The most important observation is that past realizations of six-month returns and *SUE* predict returns in the subsequent period. In particular, the two-way sort generated large differences in returns between stocks that were jointly ranked highest and stocks jointly ranked lowest. For example, the highest ranked portfolio outperformed the lowest ranked portfolio by 8.1 % in the first six months and 11.5 % in the first year.

Each variable (*R*6 and *SUE*) contributed some incremental predictive power for future returns. In Panel A, when prior returns were held fixed, stocks with high *SUE*s earned 4.3% more, on average, than stocks with low SUEs in the first six months following portfolio formation. In comparison, the returns on stocks with high and low past prior returns but similar levels of *SUE* differed on average by only 3.1%. In the first six months, the marginal contribution of *SUE* was larger than that of past returns. When the returns over the first year after portfolio formation are considered, however, a different picture emerges. The marginal contribution of *SUE* was only 3.8%, compared with a contribution of 7% for past returns.

A similar picture emerges from the two-way classification by past six-month returns and analyst forecast revisions (Panel B of Table 13). The marginal contribution of analyst revisions in the first six months was 3.8 %, compared with 4.5 % for past returns. Although the marginal contribution of analyst revisions remained at about the same level 12 months after portfolio formation, the marginal contribution of past returns increased to 9.2%.

It is possible that SUE and analyst earnings forecast revisions capture the same information. For instance, Stickel (1989) finds that analyst revision of earnings forecasts is concentrated around earnings announcements. Since forecast revisions tend to be in the same direction as the surprises in quarterly earnings announcements, it is important to examine whether these analyst forecast revisions and SUE capture the same effect. Chan, et al. address this issue and Table 13, Panel C presents their results. The results indicate that both *SUE* and analyst forecast revisions make individual contributions to return predictability, and their level of contribution is about the same. The marginal contribution of *SUE* is 3.4% and 3.7 % for 6 and 12 months, respectively, after portfolio formation. The corresponding contributions of analyst revisions are 3.2% and 4.3%.

Overall, none of the momentum variables considered here subsumes any of the others. Instead, they each exploit underreaction to different pieces of information. The results, however, indicate that the component of superior performance associated with earnings variables is more short-lived than the component associated with prior returns.

Chan, et al. propose a potential explanation for the relative longevity of the predictive component of the different types of information.  The earnings momentum strategies are based on the performance of near-term income—the surprises in quarterly earnings or changes in analysts' forecasts of earnings for the current fiscal year. In contrast, when stocks are ranked on the basis of high or low prior returns, the extreme portfolios comprise stocks for which the market made very large revisions in its expectations for the company's future outlook. The stocks in the highest ranked portfolio in the return momentum strategy rose in price by roughly 70%, on average, and the stocks in the lowest ranked portfolio fell in price by about 30%, on average, over the ranking period. Changes of this magnitude are unlikely to have arisen solely from quarter-to-quarter news in earnings. Chan, et al. report that the corresponding past six-month returns of the portfolio ranked highest (lowest) by analyst revisions is about 25 percent (–7 percent). Because the reappraisal of market beliefs for the price momentum portfolios was larger and given that the market's adjustment was not immediate, it is not surprising that the spread in future returns was larger for the price momentum strategy.

## 7. Conclusion

Underlying the efficient market hypothesis is the notion that if any predictable patterns exist in returns, investors will quickly act to exploit them, until the source of predictability is eliminated. However, this does not seem to be the case for either stock return or earnings based momentum strategies. Both strategies have been well-known and were well-publicized by at least the early 1990s, but both continue to generate excess profits.

The momentum effect is quite pervasive and it is very unlikely that it can be explained by risk. The profits from momentum strategies have generated consistently positive returns for at least the last 60 years in the United States including the 1990s, a period that was not included in the original momentum tests. Momentum profits have also been found in most major developed markets throughout the world. The only notable exception is Japan, where there is very weak and statistically insignificant evidence of momentum.

We would argue that the momentum effect represents perhaps the strongest evidence against the efficient markets hypothesis. For this reason it has attracted substantial research, which documents more details about the anomaly, e.g., the extent that momentum profits are correlated with stock characteristics, as well as attempts to provide behavioral explanations for the phenomena. At this point, we have a number of interesting facts to explain as well as possible theoretical explanations. However, financial economists are far from reaching a consensus on what generates momentum profits, making this an interesting area for future research.

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**Table 1**

**Returns of Relative Strength Portfolios**

The relative strength portfolios are formed based on *J* and *K* for the different strategies as indicated in the first column and row, respectively. The stocks are ranked in ascending order on the basis of *J* month lagged returns and an equally weighted portfolio of stocks in the lowest past return decile is the *buy* portfolio. The average monthly returns of these portfolios are resented in this table. The relative strength portfolios in Panel A are formed immediately after the lagged returns are measured for the purpose of portfolio formation. The relative strength portfolios in Panel B are formed 1 week after the lagged returns used for forming these portfolios are measured. The *t*-statistics are reported in parentheses. The sample period is January 1965 to December 1989.

| | | | Panel A | | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| J | | *K*= | 3 | 6 | 9 | 12 | *K*= | 3 | 6 | 9 | 12 |
| 3 | Sell | | 0.0108 | 0.0091 | 0.0092 | 0.0087 | | 0.0083 | 0.0079 | 0.0084 | 0.0083 |
| | | | (2.16) | (1.87) | (1.92) | (1.87) | | (1.67) | (1.64) | (1.77) | (1.79) |
| 3 | Buy | | 0.0140 | 0.0149 | 0.0152 | .0156 | | 0.0156 | 0.0158 | 0.0158 | 0.0160 |
| | | | (3.57) | (3.78) | (3.83) | (3.89) | | (3.95) | (3.98) | (3.96) | (3.98) |
| 3 | Buy- | | 0.0032 | 0.0058 | 0.0061 | 0.0069 | | 0.0073 | 0.0078 | 0.0074 | 0.0077 |
| | sell | | (1.10) | (2.29) | (2.69) | (3.53) | | (2.61) | (3.16) | (3.36) | (4.00) |
| 6 | Sell | | 0.0087 | 0.0079 | 0.0072 | 0.0080 | | 0.0066 | 0.0068 | 0.0067 | 0.0076 |
| | | | (1.67) | (1.56) | (1.48) | (1.66) | | (1.28) | (1.35) | (1.38) | (1.58) |
| 6 | Buy | | 0.0171 | 0.0174 | 0.0174 | 0.0166 | | 0.0179 | 0.0178 | 0.0175 | 0.0166 |
| | | | (4.28) | (4.33) | (4.31) | (4.13 | | (4.47) | (4.41) | (4.32) | (4.13) |
| 6 | Buy- | | 0.0084 | 0.0095 | 0.0102 | 0.0086 | | 0.0114 | 0.0110 | 0.0108 | 0.0090 |
| | Sell | | (2.44) | (3.07) | (3.76) | (3.36) | | (3.37) | (3.61) | (4.01) | (3.54) |
| 9 | Sell | | 0.0077 | 0.0065 | 0.0071 | 0.0082 | | 0.0058 | 0.0058 | 0.0066 | 0.0078 |
| | | | (1.47) | (1.29) | (1.43) | (1.66) | | (1.13) | (1.15) | (1.34) | (1.59) |
| 9 | Buy | | 0.0186 | 0.0186 | 0.0176 | 0.0164 | | 0.0193 | 0.0188 | 0.0176 | 0.0164 |
| | | | (4.56) | (4.53) | (4.30) | (4.03) | | (4.72) | (4.56) | (4.30) | (4.04) |
| 9 | Buy- | | 0.0109 | 0.0121 | 0.0105 | 0.0082 | | 0.0135 | 0.0130 | 0.0109 | 0.0085 |
| | Sell | | (3.03) | (3.78) | (3.47) | (2.89) | | (3.85) | (4.09) | (3.67) | (3.04) |
| 12 | Sell | | 0.0060 | 0.0065 | 0.0075 | 0.0087 | | 0.0048 | 0.0058 | 0.0070 | 0.0085 |
| | | | (1.17) | (1.29) | (1.48) | (1.74) | | (0.93) | (1.15) | (1.40) | (1.71) |
| 12 | Buy | | 0.0192 | 0.0179 | 0.0168 | 0.0155 | | 0.0196 | 0.0179 | 0.0167 | 0.0154 |
| | | | (4.63) | (4.36) | (4.10) | (3.81) | | (4.73) | (4.36) | (4.09) | (3.79) |
| 12 | Buy- | | 0.0131 | 0.0114 | 0.0093 | 0.0068 | | 0.0149 | 0.0121 | 0.0096 | 0.0069 |
| | Sell | | (3.74) | (3.40) | (2.95) | (2.25) | | (4.28) | (3.65) | (3.09) | (2.31) |

**Table 2**

**Returns of Relative Strength Portfolios (European)**

At the end of each month all stocks are ranked in ascending order based on previous J-month performance. The stocks in the bottom decile (lowest previous performance) are assigned to the Loser portfolio, those in the top decile to the Winner portfolio. The portfolios are initially equally weighted and held for K months. The table gives the average monthly buy-and-hold returns on those portfolios for the period 1980 – 1995. In Panel A the portfolios are formed immediately after ranking, in Panel B the portfolio formation occurs one month after the ranking takes place. T-stat is the average return divided by its standard error. The sample consists of monthly total returns in local currency for 2,190 firms in 12 European countries (Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, and The United Kingdom and consists of between 60 and 90 percent of each country's market capitalization.

| | | | Panel A | | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| J | | K= | 3 | 6 | 9 | 12 | K= | 3 | 6 | 9 | 12 |
| 3 | Loser | | 0.0116 | 0.0104 | 0.0108 | 0.0109 | | 0.0077 | 0.0087 | 0.0094 | 0.0105 |
| | Winner | | 0.0187 | 0.0192 | 0.0190 | 0.0191 | | 0.0185 | 0.0191 | 0.0190 | 0.0184 |
| | Winner - Loser | | 0.0070 | 0.0088 | 0.0082 | 0.0082 | | 0.0109 | 0.0105 | 0.0095 | 0.0079 |
| | t-stat | | (2.59) | (3.86) | (4.08) | (4.56) | | (4.29) | (4.74) | (4.99) | (4.64) |
| 6 | Loser | | 0.0095 | 0.0090 | 0.0092 | 0.0104 | | 0.0072 | 0.0076 | 0.0088 | 0.0106 |
| | Winner | | 0.0208 | 0.0206 | 0.0204 | 0.0195 | | 0.0204 | 0.0205 | 0.0200 | 0.0187 |
| | Winner - Loser | | 0.0113 | 0.0116 | 0.0112 | 0.0091 | | 0.0131 | 0.0128 | 0.0112 | 0.0081 |
| | t-stat | | (3.60) | (4.02) | (4.35) | (3.94) | | (4.27) | (4.59) | (4.50) | (3.62) |
| 9 | Loser | | 0.0088 | 0.0083 | 0.0097 | 0.0111 | | 0.0064 | 0.0077 | 0.0095 | 0.0114 |
| | Winner | | 0.0212 | 0.0213 | 0.0204 | 0.0193 | | 0.0209 | 0.0207 | 0.0197 | 0.0184 |
| | Winner - Loser | | 0.0124 | 0.0129 | 0.0107 | 0.0082 | | 0.0145 | 0.0130 | 0.0102 | 0.0070 |
| | t-stat | | (3.71) | (4.19) | (3.78) | (3.19) | | (4.50) | (4.36) | (3.77) | (2.83) |
| 12 | Loser | | 0.0084 | 0.0094 | 0.0108 | 0.0121 | | 0.0077 | 0.0093 | 0.0110 | 0.0125 |
| | Winner | | 0.0219 | 0.0209 | 0.0197 | 0.0185 | | 0.0208 | 0.0198 | 0.0188 | 0.0176 |
| | Winner - Loser | | 0.0135 | 0.0115 | 0.0089 | 0.0064 | | 0.0131 | 0.0105 | 0.0078 | 0.0051 |
| | t-stat | | (3.97) | (3.66) | (3.07) | (2.40) | | (4.03) | (3.48) | (2.80) | (1.98) |

Source: Rouwenhorst (1998)

**Table 3**

**Momentum portfolio Returns in January and outside January**

This table reports the average monthly momentum portfolio returns. The sample includes all stocks traded on the NYSE, AMEX, or Nasdaq excluding stocks priced less than $5 at the beginning of the holding period and stocks in smallest market cap decile (NYSE size decile cut off). The momentum portfolios are formed based on past six-month returns and held for six months. P1 is the equal-weighted portfolio of ten percent of the stocks with the highest past six-month returns and P10 is the equal-weighted portfolio of the ten percent of the stocks with the lowest past six-month returns.

| | | P1 | P10 | P1-P10 | *t*-statistic | Percent Positive |
|---|---|---|---|---|---|---|
| 1965-1998 | Jan | 3.40 | 4.95 | -1.55 | -1.87 | 29 |
| | Feb-Dec | 1.49 | 0.01 | 1.48 | 7.89 | 69 |
| | All | 1.65 | 0.42 | 1.23 | 6.46 | 66 |

**Table 4**

**Portfolio Characteristics.**

This table reports the characteristics of momentum portfolios. The sample includes all stocks traded on the NYSE, AMEX, or Nasdaq excluding stocks priced less than $5 at the beginning of the holding period and stocks in smallest market cap decile (NYSE size cut off). P1 is the equal-weighted portfolio of ten percent of the stocks with the highest past six-month returns, P2 is the equal-weighted portfolio of the ten percent of the stocks with the next highest past six-month returns and so on. Average size decile rank is the average rank of the market capitalization of equity (based on NYSE size decile cut offs) of the stocks in each portfolio at the beginning of the holding period. FF factor sensitivities are the slope coefficients in the Fama-French three-factor model time-series regressions. ``Market'' is the market factor, ``SMB'' is the size factor and ``HML'' is the book-to-market factor. The sample period is January 1965 to December 1998.

| | Average size decile rank | FF factor sensitivities | | |
|---|---|---|---|---|
| | | Market | SMB | HML |
| P1 | 4.81 | 1.08 | 0.41 | -0.24 |
| P2 | 5.32 | 1.03 | 0.23 | 0.00 |
| P3 | 5.49 | 1.00 | 0.19 | 0.08 |
| P4 | 5.51 | 0.99 | 0.17 | 0.14 |
| P5 | 5.49 | 0.99 | 0.17 | 0.17 |
| P6 | 5.41 | 0.99 | 0.19 | 0.19 |
| P7 | 5.36 | 0.99 | 0.22 | 0.19 |
| P8 | 5.26 | 1.01 | 0.24 | 0.16 |
| P9 | 5.09 | 1.04 | 0.30 | 0.11 |
| P10 | 4.56 | 1.12 | 0.55 | -0.02 |
| P1-P10 | 0.25 | -0.04 | -0.13 | -0.22 |

**Table 5**

**CAPM and Fama-French Alphas**

This table reports the risk-adjusted returns of momentum portfolios. The sample comprises all stocks traded on the NYSE, AMEX, or Nasdaq excluding stocks priced less than $5 at the beginning of the holding period and stocks in smallest market cap decile (NYSE size decile cut off). P1 is the equal-weighted portfolio of ten percent of the stocks with the highest past six-month returns, P2 is the equal-weighted portfolio of the ten percent of the stocks with the next highest past six-month returns and so on. This table reports the intercepts from the market model regression (CAPM Alpha) and Fama-French three-factor regression (FF Alpha). The sample period is January 1965 to December 1998. The *t*-statistics are reported in parentheses.

| | CAPM Alpha | FF Alpha |
|---|---|---|
| P1 | 0.46<br>(3.03) | 0.50<br>(4.68) |
| P2 | 0.29<br>(2.86) | 0.22<br>(3.51) |
| P3 | 0.21<br>(2.53) | 0.10<br>(2.31) |
| P4 | 0.15<br>(1.92) | 0.02<br>(.41) |
| P5 | 0.13<br>(1.70) | -0.02<br>(-.43) |
| P6 | 0.10<br>(1.22) | -0.06<br>(-1.37) |
| P7 | 0.07<br>(.75) | -0.09<br>(-1.70) |
| P8 | -0.02<br>(-.19) | -0.16<br>(-2.50) |
| P9 | -0.21<br>(-1.69) | -0.33<br>(-4.01) |
| P10 | -0.79<br>(-4.59) | -0.85<br>(-7.54) |
| | | |
| P1-P10 | 1.24<br>(6.50) | 1.36<br>(-7.04) |

Source: Jegadeesh and Titman (2001a)

**Table 6**

**Real and Random Industry Momentum Strategies**

Each month *t*, all NYSE and AMEX stocks are assigned to 1 of 20 industry portfolio, I, which are ranked according to the criterion $\sum_{t=t-7}^{t-2} r_{It}$ , where $r_{It}$ ,is the month *t* return on industry *1*. The real industry momentum strategy then designates winners and losers as the top and bottom three industries from this ranking. Portfolios are formed monthly. The sample period is July 1963 through July 1995 (385 months). The random industry momentum strategy maintains the portfolio weights within each winner and loser industry for month *t* but each stock *j* in a winner or loser portfolio is replaced by the stock ranking one place higher than stock *j* when all NYSE and AMEX stocks *i* are ranked according to the criterion. The strategy for individual stocks ranks stocks based on their returns over the ranking periods and the top ten percent are assigned to the winner portfolio and bottom ten percent are assigned to the loser portfolio. Panel B presents the results for ranking period *t* – 6 through *t* – 1.

| | Real industry strategy | | | Random industry strategy | | | Individual stocks | | |
|---|---|---|---|---|---|---|---|---|---|
| | Overall | January | NonJan | Overall | January | NonJan | Overall | January | NonJan |
| A. Formation period for month *t* is *t* –7,…, *t* - 2 | | | | | | | | | |
| Value weighting | | | | | | | | | |
| Mean (%) | 0.16 | -0.90 | 0.26 | -0.01 | -2.37 | 0.21 | --- | --- | --- |
| SD (%) | 4.09 | 4.95 | 3.99 | 3.42 | 5.15 | 3.15 | | | |
| *t*-statistic | (0.79) | (-1.03) | (1.23) | (-0.03) | (-2.61) | (1.25) | | | |
| Equal weighting | | | | | | | | | |
| | 0.37 | -1.24 | 0.52 | 0.07 | -1.65 | 0.22 | 0.76 | -7.79 | 1.54 |
| | 3.51 | 4.76 | 3.34 | 1.90 | 2.55 | 1.76 | 5.95 | 10.99 | 4.55 |
| | (2.09) | (-1.47) | (2.92) | (0.71) | (-3.66) | (2.40) | (2.39) | (-3.82) | (6.04) |
| B. Formation period for month *t* is *t* – 6 ,…, *t* - l | | | | | | | | | |
| Value weighting | | | | | | | | | |
| | 0.47 | -0.34 | 0.55 | 0.00 | -1.31 | 0.12 | | | |
| | 4.10 | 5.10 | 4.00 | 3.55 | 5.60 | 3.29 | | | |
| | (2.27) | (-0.38) | (2.57) | (0.00) | (-1.33) | (0.68) | | | |
| Equal weighting | | | | | | | | | |
| | 0.78 | -0.42 | 0.89 | -0.01 | -1.45 | 0.12 | | | |
| | 3.54 | 4.86 | 3.38 | 1.79 | 2.52 | 1.66 | | | |
| | (4.30) | (-0.49) | (4.92) | (-0.10) | (-3.26) | (1.39) | | | |

Source: Table 3 and Table 4 of Grundy and Martin (2001)

## Table 7

## Monthly Returns for Portfolios Based on Price Momentum and Analyst Coverage

This table includes only stocks above the NYSE/AMEX 20th percentile. The relative momentum portfolios are formed based on 6-month lagged raw returns and held for 6 months. The stocks are ranked in ascending order on the basis of 6-month lagged returns. Portfolio P1 is an equally-weighted portfolio of stocks in the worst performing 30%, portfolio P2 includes the middle 40% and portfolio P3 includes the best performing 30%. This table reports the average monthly returns of these portfolios and portfolios formed using an independent sort on Model 1 analyst coverage residuals of log size and a NASDAQ dummy (see cited paper). The least covered firms are in Sub1, the medium covered firms in Sub 2, the most covered firms in Sub3. Mean (median) size is in millions. T-stats are in parentheses.

| | | Residual Coverage Class | | | |
|---|---|---|---|---|---|
| Past | All Stocks | Low:Sub1 | Medium:Sub2 | High:Sub3 | Sub1-Sub3 |
| P1 | 0.00622 | 0.00271 | 0.00669 | 0.00974 | -0.00703 |
| | (1.54) | (0.66) | (1.70) | (2.31) | (-5.16) |
| P2 | 0.01367 | 0.01257 | 0.01397 | 0.01439 | -0.00182 |
| | (4.40) | (4.20) | (4.58) | (4.29) | (-2.11) |
| P3 | 0.01562 | 0.01402 | 0.01583 | 0.01690 | -0.00288 |
| | (4.35) | (3.95) | (4.52) | (4.45) | (-2.80) |
| P3 – P1 | 0.00940 | 0.01131 | 0.00915 | 0.00716 | 0.00415 |
| | (4.89) | (5.46) | (4.64) | (3.74) | (3.50) |
| | | | | | |
| Mean Size | | 962 | 986 | 455 | |
| Median Size | | 103 | 200 | 180 | |
| Mean Analyst | | 1.5 | 6.7 | 9.7 | |
| Median Analyst | | 0.1 | 3.5 | 7.6 | |

Source: Hong, Lim and Stein (1998)

**Table 8**

**Returns of Size, Book-To-Market and Momentum Sorted Portfolios**

For this table all listed common stocks from the NYSE, AMEX and NASDAQ are sorted into three quintile groupings based on market capitalization, book-to-market ratio and prior-year return. Panel A presents the average returns of 25 size/book-to-market sorted portfolios over the 1963:07 – 1997:12 period. These 25 portfolios are formed by equally weighting the five corresponding size-sorted portfolios. Panel B examines similar strategies that exclude the largest and smallest quintile stocks.

**Panel A**: Raw Returns, All Quintiles

| | *Low* | | **BM** | | *High* | H – L | t-stat |
|---|---|---|---|---|---|---|---|
| *Low* | 0.454 | 0.713 | 1.067 | 1.166 | 1.389 | 0.935 | (5.286) |
| | 0.728 | 0.980 | 1.137 | 1.288 | 1.455 | 0.727 | (4.748) |
| **Past returns** | 0.922 | 1.058 | 1.174 | 1.298 | 1.369 | 0.447 | (2.730) |
| | 1.043 | 1.141 | 1.162 | 1.364 | 1.400 | 0.357 | (1.930) |
| *High* | 1.206 | 1.418 | 1.369 | 1.511 | 1.494 | 0.288 | (1.449) |
| H – L | 0.752 | 0.705 | 0.302 | 0.345 | 0.105 | HH-LL | |
| t-stat | (3.838 | (4.027) | (1.866) | (2.180) | (0.587) | 1.0398 | (5.656) |

**Panel A**: Raw Returns, Quintiles 2-4 only

| | *Low* | | **BM** | | *High* | H – L | t-stat |
|---|---|---|---|---|---|---|---|
| *Low* | 0.550 | 0.651 | 1.064 | 1.159 | 1.527 | 0.977 | (5.019) |
| | 0.686 | 0.966 | 1.159 | 1.174 | 1.506 | 0.820 | (4.625) |
| **Past returns** | 0.900 | 1.025 | 1.120 | 1.330 | 1.419 | 0.519 | (2.738) |
| | 1.003 | 1.098 | 1.149 | 1.398 | 1.430 | 0.427 | (1.998) |
| *High* | 1.341 | 1.503 | 1.406 | 1.516 | 1.606 | 0.265 | (1.113) |
| H – L | 0.792 | 0.852 | 0.342 | 0.357 | 0.080 | HH-LL | |
| t-stat | (3.329) | (4.255) | (1.959) | (2.130) | (0.424) | 1.0566 | (5.022) |

Source: Daniel and Titman (1999)

**Table 9**

**Monthly Returns for Portfolios Based on Price Momentum and Trading Volume**

This table presents average monthly returns from portfolio strategies based on an independent two-way sort based on past returns and past average daily turnover for the 1964 to 1995 time period. At the beginning of each month all available stocks in the NYSE/AMEX are sorted independently based on past 6 month returns and divided into 10 portfolios. R1 represents the *loser* portfolio and R10 represents the *winner* portfolio. The stocks are then independently sorted based on average daily volume over the past 6 months and divided into three portfolios, where turnover is used as a proxy of trading volume. V1 represents the lowest trading volume portfolio and V3 represents the highest trading volume portfolio. The stocks at the intersection of the two sorts are grouped together to form portfolios based on past returns and past trading volume. Monthly returns are computed as an equal-weighted average of returns from strategies initiated at the beginning of this month and past months. The numbers in parentheses are simple t-statistics.

| | V1 | V2 | V3 | V3 – V1 |
|---|---|---|---|---|
| R1 | 1.12 | 0.67 | 0.09 | -1.04 |
| | (2.74) | (1.61) | (0.20) | (-5.19) |
| R10 | 1.67 | 1.78 | 1.55 | -0.12 |
| | (5.30) | (5.41) | (4.16) | (-0.67) |
| R10 – R1 | 0.54 | 1.11 | 1.46 | 0.91 |
| | (2.07) | (4.46) | (5.93) | (4.61) |

Source: Lee and Swaminathan (2000)

**Table 10: Returns for Portfolios Formed Based on Standardized Unexpected Earnings (SUE).**

This table presents the returns of extreme SUE portfolios reported in various papers. SUE is defined as.

$$SUE = \frac{\text{Quarterly earnings} - \text{Expected quarterly earnings}}{\text{Standard deviation of quarterly earnings}}.$$

The High and Low SUE portfolios in Latane and Jones (1969) are comprise stocks with SUE greater than 2 and less than -2 respectively. The High and Low SUE portfolios in Bernard and Thomas (1989) and Chan, Jegadeesh and Lakonishok (1996) comprise the decile of stocks with the highest and lowest SUE respectively. Latane and Jones, and Bernard and Thomas report abnormal returns and Chan, et al. report raw returns.

| Paper | Sample period | Holding Period | Sample | Returns | | |
|---|---|---|---|---|---|---|
| | | | | High SUE | Low SUE | Difference |
| Latane and Jones (1979) | 1974-1977 | 6 months | All Firms | 3.1 | -4.2 | 7.3 |
| Bernard and Thomas (1989) | 1974-1986 | 120 days | Small | 2.6 | -5.4 | 8.0 |
| | | | Medium | 2.3 | -4.8 | 7.1 |
| | | | Large | 2.0 | -2.1 | 4.1 |
| Chan Jegadeesh and Lakonishok (1996) | 1973-1993 | 6 months | All Firms | 11.9 | 5.1 | 6.8 |
| | | 12 months | All Firms | 21.3 | 13.8 | 7.5 |

**Table 11: Returns for Portfolios Formed Based on Analyst Forecast Revisions**

This table presents the returns for portfolios formed based on analyst forecast revisions. The Up revision portfolio in Givoly and Lakonishok comprises stocks with analyst forecast revision greater than 5% and the Down revision portfolio comprises stocks with analyst forecast revision less than -5%. The Up and Down revision portfolios in Stickel (1991) comprise five percent of the stocks with the highest and lowest analyst forecast revisions. The top panel for Stickel presents results based on forecast revisions by individual analysts and the bottom panel presents results based on consensus earnings forecast revisions. Chan, Jegadeesh and Lakonishok rank stocks based on a six-month moving average of the ratio of analyst forecast revision to stock price. The Up and Down revision portfolios in Stickel (1991) comprise decile of stocks with the highest and lowest analyst forecast revisions. Givoly and Lakonishok, and Stickel report abnormal returns and Chan, et al. report raw returns.

| Paper | Sample period | Sample | Holding Period | Returns | | |
|---|---|---|---|---|---|---|
| | | | | Up Revisions | Down Revisions | Difference |
| Givoly and Lakonishok (1979) | 1967-1974 | 49 Firms from S&P Earnings Forecaster | 2 months | 2.7 | -1.0 | 3.7 |
| Stickel (1991) | 1981-1985 | NYSE/AMEX stocks on Zachs | 125 days | 2.99 | -4.08 | 7.07 |
| | | | | 2.83 | -3.53 | 6.36 |
| Chan, Jegadeesh and Lakonishok (1996) | 1973-1993 | NYSE/AMEX /Nasdaq stocks on IBES | 6 months | 12.3 | 4.6 | 7.7 |
| | | | 12 months | 22.9 | 13.2 | 8.7 |

**Table 12. Correlations Among Prior Six-Month Return and Earnings Momentum Variables**

| | R6[a] | SUE[b] | REV 6[c] |
|---|---|---|---|
| R6 | 1.000 | | |
| SUE | 0.293 | 1.000 | |
| REV 6 | 0.294 | 0.440 | 1.000 |

[a] *R6* is a stock's compound return over the prior six months.
[b] *SUE* is unexpected earnings (the change in the most recent past quarterly earnings per share from its value four quarters ago), scaled by the standard deviation of unexpected earnings over the past eight quarters.
[c] *REV6* is a moving average of the past six months' revisions in IBES median analyst earnings forecasts relative to beginning-of-month stock price.

(Source: Chan, Jegadeesh and Lakonishok ,1996)

**Table 13. Post Formation Returns for Portfolios Classified Based on Past Return Momentum and Earnings Momentum: Two-way Classification**

**Panel A. Standardized unexpected earnings and prior 6-month return**

| Standardized unexpected earnings | 1(Low) | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3(High) |
|---|---|---|---|---|---|---|---|---|---|
| Prior 6-month return | 1(Low) | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3(High) |
| First six months | 0.055 | 0.094 | 0.085 | 0.076 | 0.106 | 0.113 | 0.074 | 0.118 | 0.136 |
| First year | 0.142 | 0.190 | 0.157 | 0.183 | 0.224 | 0.216 | 0.190 | 0.253 | 0.257 |

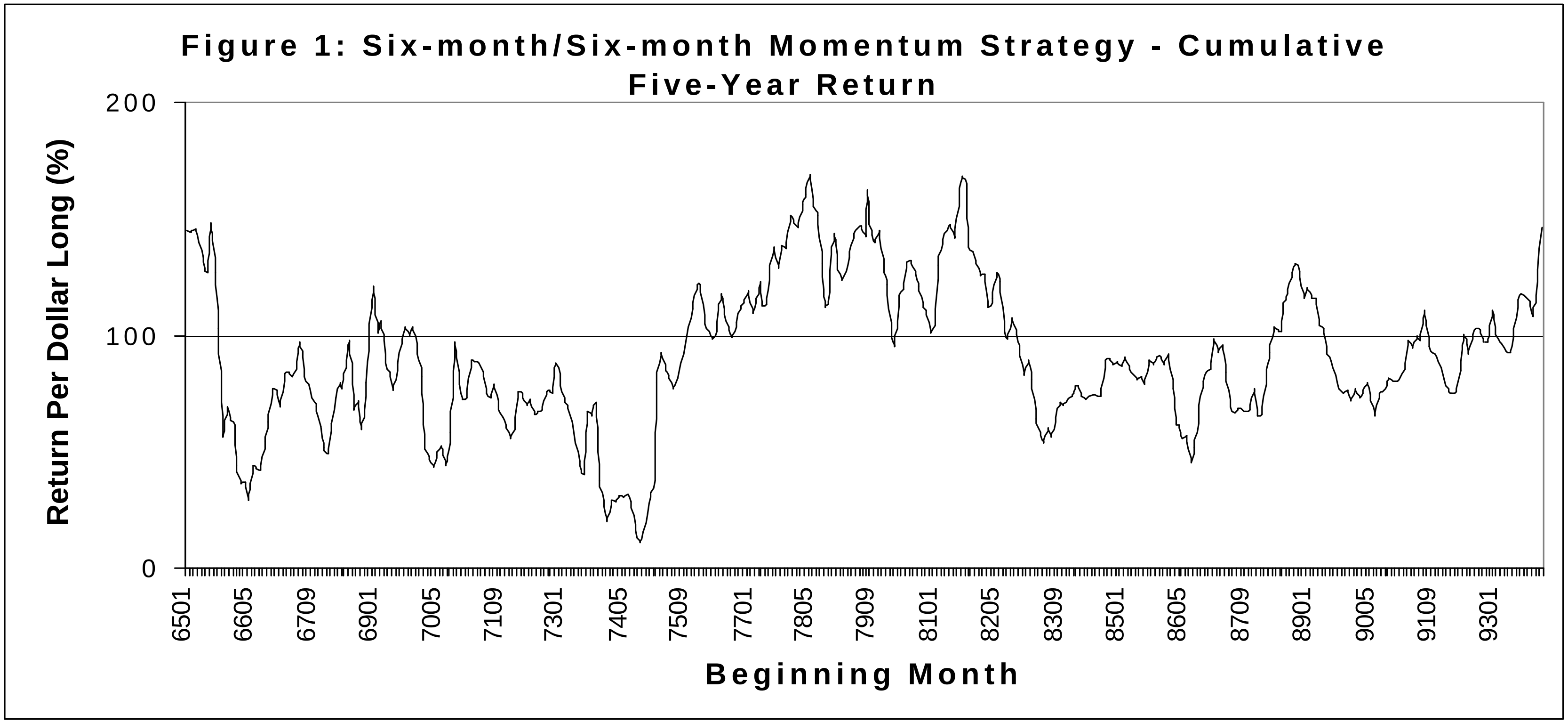
**Panel B. Revision in analyst forecasts and prior 6-month return**

| Revision in analyst forecasts | 1(Low) | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3(High) |
|---|---|---|---|---|---|---|---|---|---|
| Prior 6-month return | 1(Low) | 1 | 1 | 2 | 2 | 2 | 3 | 3 | 3(High) |
| First six months | 0.042 | 0.063 | 0.085 | 0.077 | 0.088 | 0.112 | 0.093 | 0.103 | 0.130 |
| First year | 0.113 | 0.134 | 0.152 | 0.180 | 0.186 | 0.214 | 0.214 | 0.215 | 0.246 |

**Panel C. Revision in analyst forecasts and standardized unexpected earnings**

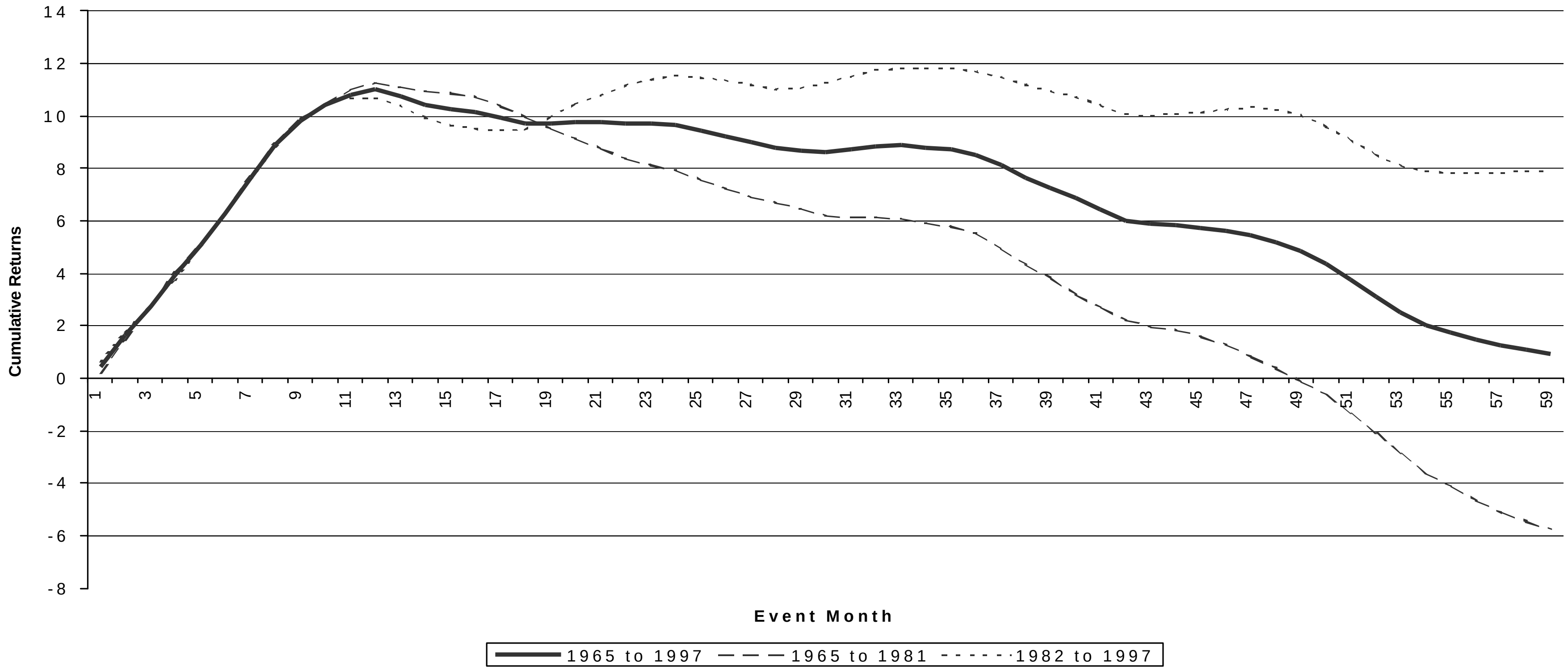
| Revision in analyst forecasts<br>Standardized unexpected earnings | 1(Low)<br>1(Low) | 2<br>1 | 3<br>1 | 1<br>2 | 2<br>2 | 3<br>2 | 1<br>3 | 2<br>3 | 3(High)<br>3(High) |
|---|---|---|---|---|---|---|---|---|---|
| First six months | 0.051 | 0.065 | 0.093 | 0.084 | 0.093 | 0.111 | 0.093 | 0.096 | 0.121 |
| First year | 0.137 | 0.153 | 0.190 | 0.184 | 0.196 | 0.224 | 0.185 | 0.187 | 0.220 |

(Source: Chan, Jegadeesh and Lakonishok ,1996)




This figure presents the cumulative five-year returns for a strategy that buys the decile of stocks that earned the highest returns over the previous six-months and sells the decile of stocks that earned the lowest returns over the previous six-months. The holding period is six months. The figure presents the cumulative returns starting from the month on the x-axis.

**Figure 2: Cumulative Momentum Profits**




This figure presents cumulative momentum portfolio returns with a sample of stocks traded on the NYSE,AMEX or Nasdaq. The sample comprises all stocks that are larger than the smallest NYSE market cap decile at the beginning of the event period. Stocks priced less that $5 at the beginning of each event month are excluded from the sample. See Table 1 for a description of momentum portfolio construction.

Source: Jegadeesh and Titman (2001a)