MOMENTUM TRADING STRATEGIES FOR INDUSTRY GROUPS: A CLOSER LOOK

by

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Ethics Approval

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ABSTRACT

This paper builds on Jegadeesh and Titman (1993) and Grinblatt and Moskowitz (1999) to take a closer look at intermediate-term momentum trading strategies for industry groups. Specifically, it is found that: momentum trading strategies for industry groups are significantly more profitable when we include more industries in the universe and purchase/sell fewer winning/losing industries in the strategy; the winner and loser portfolios are made up of cyclical industries; industry momentum peaks after a total time period (evaluation period plus holding period) of thirteen to fourteen months, regardless of the number of industries examined; returns to momentum trading strategies vary significantly throughout the year, and June and December are by far the most significant months for momentum profits; and, the winners momentum portfolio outperforms the market in 6 out of 9 *bear* markets during the sample period, even though this strategy is perceived as much riskier because of industry concentration.

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1 INTRODUCTION

This paper builds on Jegadeesh and Titman (1993) and Grinblatt and Moskowitz (1999) to take a closer look at intermediate-term momentum trading strategies as explained by industry groups. First, I show that the profitability of momentum trading strategies varies significantly with: (1) the portion of industries included in the winners and losers portfolios; and (2) the number of industries included in the universe. Second, I show that some industries appear in the winner and loser portfolios much more frequently than others, and that the industries that are most often featured in the winner and loser momentum portfolios are industries commonly referred to as 'cyclical'. Third, I show that industry momentum peaks after a total time period (evaluation period plus holding period) of thirteen to fourteen months, regardless of the number of industries examined and the length of the evaluation period. Fourth, I show that returns to the momentum trading strategies vary significantly throughout the year, and that June and December are by far the most significant months for momentum profits. Finally, I show that a zero-cost intermediate-term industry momentum trading strategy performs much differently in 'bear' markets than it does in 'bull' markets, and is surprisingly stable in times of market crisis. Further, the winners momentum portfolio outperforms the market in 6 out of 9 *bear* markets during the sample period, even though this strategy is perceived as much riskier because of industry concentration.

While intermediate-term momentum trading strategies have been a hot topic amongst investment managers for decades, it is only in the past decade or so that the academic community has accepted intermediate-term momentum as a consistently observable factor that has strong implications for the concept of market efficiency. Technical analysts have been looking at intermediate-term momentum as an element of their trading strategies for years. In fact, the 'primary trend' concept developed by Charles Dow around the end of the 19th century is based on the idea that a stock will remain in a general uptrend or downtrend for a few months to a few years at a time.[1] More recently, Gerald Appel's Moving Average Convergence Divergence ("MACD") technical indicator has been used by thousands of technical analysts to judge stock, industry or broad-market index momentum.[2] Grinblatt, Titman and Wermers (1995) find that 77% of the 155 mutual funds studied were 'momentum investors' during the 1975-1984 time period, buying stocks that were past winners (most did not systematically sell stocks that were past losers). Further, the authors find that, on average, funds that invested on momentum realized significantly better performance than other funds. However, it should be noted that this study's limited time period may have a significant effect on the results, and that we may not be able to apply similar conclusions to other time periods.

Jegadeesh and Titman (1993) reveal both the statistical and economic significance and the consistency of profits obtainable from intermediate-term momentum trading strategies. The authors examine data for NYSE and AMEX individual stocks over the 1965 to 1989 sample period and report the return results for the following trading strategy:

- Rank stocks into deciles based on their returns for various lag periods;
- Buy the winning decile of stocks/sell the losing decile of stocks; and

[1] Source: http://stockcharts.com/education/MarketAnalysis/dowtheory1.html
[2] Source: http://stockcharts.com/education/IndicatorAnalysis/indic_MACD1.html

- Hold these portfolios for various hold periods.

The authors equal-weight the stocks in the winner and loser portfolios and focus on the profits obtained from portfolios that were rebalanced monthly to maintain equal weights. The authors find statistically significant monthly returns as high as 1.31% (16.90% annual) for the zero-cost strategy that ranks stocks on their past 12-month returns, purchases the winning portfolio/sells the losing portfolio and holds for 3 months. The authors identify three potential sources of relative strength profits: the cross-sectional dispersion in expected returns, serial covariance of the momentum factor and the average serial covariance of the idiosyncratic components of security returns. The authors reject the first two of these potential sources of relative strength profits, and also reject a lead-lag effect (originally proposed by Lo and MacKinlay, 1990) as a potential source for the average serial covariance of the idiosyncratic components of security returns. They subsequently conclude that the profitability of intermediate-term momentum trading strategies is therefore related to market underreaction to firm-specific information. The authors find that the profitability of short-term momentum strategies is not confined to any particular sub-sample of stocks, as measured by firm size and ex ante estimates of beta (two commonly accepted measures of risk and expected returns). However, the results indicate that, on average, firms held in the winner and loser portfolios tend to be smaller in size and have higher betas than firms that are held in the non-winner/loser portfolios. One of the most interesting findings of Jegadeesh and Titman (1993) is the complete reversal of short-term momentum profitability in the month of January. In fact, the 6-month/6-month momentum trading strategy loses about 7.0% on average in January but achieves positive abnormal returns in each of the other months (the average return in non-January months is 1.66% per month). The economic significance of the January reversal is huge: a trading strategy that reversed the buy and sell portfolios in January would achieve 25.0% per year in abnormal (zero-cost) returns. In addition, the authors find the January reversal is by far strongest in the smallest third of stocks, and is strongly inversely related to firm size. Another key finding of Jegadeesh and Titman (1993) is that the cumulative return of the trading strategy that buys winners/sells losers based on their past 6-month performance is negative in the first month, peaks in holding month 12 and holds positive out to month 36 (and potentially beyond). This finding of negative return in the first holding month is important to note because it is not consistent with studies of industry momentum (vs. individual stock momentum). Finally, the authors back-test the momentum trading strategy for the periods 1927-1940 and 1941-1964. They find the 6-month lag strategy is unable to generate a cumulative positive return in the 1927-1940 period, and explain that this is the result of the significant 'back-and-forth' volatility that was experienced in the market at this time, without any significant sustained uptrends or downtrends. However, the results for the 1941-1964 time period are very similar to the results for the 1965-1989 time period, with the exception of the cumulative returns disappearing by holding month 24. The authors note

> the evidence of initial positive and later negative relative strength returns suggests that common interpretations of return reversals as evidence of overreaction and return persistence (i.e. momentum) as evidence of underreaction are probably overly simplistic.

They conjecture that it's possible that the market underreacts to information about the short-term prospects of firms but overreacts to information about their long-term prospects, thereby causing intermediate-term momentum and long-term mean reversion (long-term mean reversion is well-documented in De Bondt and Thaler, 1995).

Jegadeesh and Titman (1995) take a closer look at the source of short-term contrarian profits. This study builds on the finding of Jegadeesh and Titman (1993) that returns to intermediate-term momentum strategies are negative in the first month, i.e. prices exhibit short-term reversal. The authors posit two sources of short-term contrarian profits: delayed stock price reaction to common factors (the lead-lag effect) and overreaction to firm-specific information. The results of their tests indicate that stock prices on average react with a delay to common factors, but overreact to firm-specific information. The find, however, that the delayed reactions contribute little to contrarian profits, and that most of the short-horizon contrarian profits arise because of the tendency of stock prices to overreact to firm-specific information.

Chan, Jegadeesh and Lakonishok (1996) relate the evidence on momentum in stock prices to the evidence on the market's underreaction to earnings-related and other information. They note that studies have found that firms reporting unexpectedly high earnings outperform firms reporting unexpectedly poor earnings. The superior performance persists over a period of about six months after earnings announcements. The authors put forward the following:

1. The profitability of momentum strategies may be due to the component of medium-horizon returns that is related to earnings-related news. If this explanation is true, then momentum strategies will not be profitable after accounting for past innovations in earnings and earnings forecasts.

2. The profitability of momentum strategies stems from overreaction induced by positive-feedback trading strategies, i.e. that 'trend-chasers' reinforce movements in stock prices even in the absence of fundamental information, so that the returns for past winners and losers are (at least partly) temporary in nature. Under this explanation, they expect that past winners and losers will subsequently experience reversals in their stock prices.

3. Strategies based either on past returns or on earnings surprises (earnings momentum) exploit market under-reaction to different pieces of information. For example, an earnings momentum strategy may benefit from underreaction to information related to short-term earnings, while a price momentum strategy may benefit from the market's slow response to a broader set of information, including long-term profitability. In this case they would expect that each of the momentum strategies is individually successful, and that one effect is not subsumed by the other.

The authors confirm that drifts in future returns over the next six and twelve months are predictable from a stock's prior return and from prior news about earnings. Each momentum variable has separate explanatory power for future returns, so one strategy does not subsume the other. Also, there is little sign of subsequent reversals in returns, suggesting that positive feedback trading cannot account for the profitability of momentum strategies. However, the authors find evidence of subsequent correction in prices when large, positive prior returns are not validated by good news about earnings. The authors also find that a substantial portion of the momentum effect is concentrated around subsequent earnings announcements. They conclude that the bulk of evidence thus points to a delayed reaction of stock prices to the information in past returns and in past earnings. They also note that their evidence that the market's response to news takes time is not an entirely negative verdict on the informational efficiency of the stock market. Prior news has already caused a substantial realignment in stock prices over the preceding period (six months in this study). The past adjustment produces differences in returns of roughly 100 percent between the most-favourably and least-favourably affected stocks. The remaining adjustment that is left on the table for investors is small in comparison.

Fama and French (1996) attempt to explain intermediate-term momentum and long-term reversion in stocks prices using their three-factor model, which includes the excess return on the market (R_M - R_F), the return of small stocks minus large stocks (SMB) and the return of high-book-to-market stocks minus low-book-to-market stocks (HML). The three factor model finds higher excess returns for stocks that load high on the SMB and HML factors, i.e. stocks that are small and have high book-to-market ratios. They are able to explain long-term reversion in stock prices (skipping the year prior to portfolio formation, i.e. the intermediate-term momentum period) with their three-factor model because long-term losers (subsequent winners) tend to have high factor loadings on SMB and HML and long-term winners (subsequent losers) tend to have low factor loadings on SMB and HML. However, they are unable to explain intermediate-term momentum because intermediate-term losers (subsequent losers) tend to have high factor loadings on SMB and HML and intermediate-term winners (subsequent winners) tend to have low factors loadings on SMB and HML. It is important to note that when portfolios are formed on long-term past returns that include the year prior to portfolio formation (the intermediate-momentum period), intermediate-term continuation offsets long-term reversal, leaving either continuation or little pattern in future returns.

Conrad and Kaul (1998) point out that most return-based strategies implemented in the literature rely exclusively on the existence of time-series patterns in returns. They note the following,

> Specifically, all such strategies are based on the premise that stock prices do not follow random walks. However, the actual profits to the trading strategies implemented based on past performance contain a cross-sectional component that would arise even if stock prices are completely unpredictable and do follow random walks. Consider, for example, a momentum strategy. The repeated purchase of winners from the proceeds of the sale of losers will, on average, be tantamount to the purchase of high-mean securities from the sale of low-mean securities. Consequently, as long as there is some cross-sectional dispersion in the mean returns of the universe of securities, a momentum strategy will be profitable.

However, there is no reason to believe a portfolio of winners is a portfolio of high-mean securities, i.e. there is no theoretical reason to believe that the past performance of a security indicates anything about its future performance. Conrad and Kaul's statement depends on the assumption of mean stationarity of the returns of individual securities during the period in which the strategies are implemented. However, as later studies would point out, this assumption does not hold. Conrad and Kaul use a single framework to analyze the sources of profits to a wide spectrum of return-based trading strategies implemented in the literature (including momentum and contrarian strategies). When they ex post condition on the return horizon of the strategy and/or the subperiod during which it is implemented, two patterns emerge that are consistent with the literature on returns-based trading strategies. The momentum strategy usually nets positive, and frequently statistically significant, profits at medium (3-12 month) horizons, except during the 1926-1947 subperiod, while a contrarian strategy is successful at long horizons, although the profits to these strategies are statistically significant only during the 1926-1947 subperiod.

Rouwenhorst (1998) addresses the concern that apparent momentum anomalies are simply the outcome of an elaborate data snooping process by studying return patterns in an international context. He focuses on international medium-term return continuation within markets and across markets at the individual stock level using a sample of 2,190 stocks from 12 European countries in the period 1978 to 1995. He finds that an internationally diversified relative strength portfolio that invests in past medium-term winners and sells past medium-term losers earns approximately 1.0 percent per month. This momentum in returns is not limited to a particular market, but is present in all 12 markets in the sample. It holds across size deciles, although return continuation is stronger for small than large firms. The outperformance lasts for about one year, and cannot be attributed to conventional measures of risk. In fact, controlling for market risk or exposure to a size factor increases the abnormal performance of relative strength strategies. However, Rouwenhorst presents some evidence that European and U.S. momentum strategies have a common component, which suggests that exposure to a common factor may drive the profitability of momentum strategies. He concludes that it is unlikely that the U.S. experience with momentum strategies was simply due to chance.

Grinblatt and Moskowitz (1999) find a strong and prevalent momentum effect in industry components of stock returns which accounts for much of the individual stock momentum anomaly. Using the CRSP and COMPUSTAT data files (including NYSE, AMEX and Nasdaq stocks), 20 value-weighted industry portfolios are formed for every month from July 1963 to July 1995. The average number of stocks per industry is 230, and the fewest number of stocks at any time in any industry except Railroads is more than 25 (to ensure diversification of firm-specific risk). An F-test of whether the sample-mean returns differ across industries is not rejected, suggesting that there is little cross-sectional variation in the industry sample means. Grinblatt and Moskowitz build on Jegadeesh and Titman (1993) by suggesting there are four sources of momentum trading profits from individual stocks:

1. The cross-sectional variation in unconditional mean returns;
2. Serial correlation in the factor portfolios, i.e. portfolios formed on book-to-market, size or market beta;
3. Serial correlation in industry return components; and
4. Serial covariation in firm-specific components.

They note that the Jegadeesh and Titman (1993) suggestion that the serial correlation in components of returns that are not related to factors is primarily responsible for momentum trading profits is the equivalent of asserting that either the serial correlation in industry return components or the serial covariation in firm-specific components, or both, generate momentum. Grinblatt and Moskowitz employ the same technique as Jegadeesh and Titman (1993) to avoid test statistics that are based on overlapping returns. This technique involves repeating the strategy monthly, so as to have multiple portfolios contributing to any one month's return. Using this technique, it would be wrong to attribute more than a negligible portion of any one month's return to bid-ask bounce (in the case of individual stock momentum) or a lead-lag effect (in the case of industry momentum). To begin with, the authors run an individual stock momentum strategy by sorting stocks on their past six-month returns, purchasing the winning 30% of stocks and shorting the losing 30% of stocks, and holding this portfolio for six months. The strategy is repeated monthly and portfolios are rebalanced monthly to equal weights. This strategy generates a return (per dollar long) of 0.43 percent per month, which is lower but statistically more significant than the momentum-based portfolio return reported in Jegadeesh and Titman (1993). The authors then move onto an industry momentum strategy. They find that sorting industry portfolios (which value-weight stocks within the industry) based on their past six-month returns, and investing equally in the top three (15%) industries while shorting equally the bottom three (15%) industries (holding this position for six months) produces average monthly profits of 0.43 percent - identical in magnitude to those obtained from the momentum strategy for individual equities. However, the authors fail to note that the proportion of industries the industry momentum strategy purchased and sold was smaller than the proportion of stocks the individual stock momentum strategy purchased and sold. We might expect that purchasing and selling a smaller proportion of the 'units' (stocks/industries) involved would lead to a higher return on the strategy (given all else is equal). Grinblatt and Moskowitz find that the covariance of consecutive nonoverlapping six-month returns on an equal-weighted, monthly rebalanced index is insignificantly different from zero. Further, none of the serial covariances for consecutive six-month returns of each of the three Fama and French (1993) factor-mimicking portfolios is significantly different from zero. Thus, persistence in the returns represented by the factors is not driving momentum-trading profits. The authors go on to argue that the existence of industry momentum profits of the same magnitude as individual stock momentum profits suggests that dispersion in unconditional mean returns does not drive momentum profits. The cross-sectional variance of ex post mean industry monthly returns is only 0.00083, which is far less than the estimated cross-sectional dispersion of historical mean monthly stock returns of 0.011. Moreover, the failure to reject an F-test that ex ante mean industry returns are equal suggests that the cross-sectional dispersion in unconditional industry mean returns is small. They conclude that the existence of industry momentum profits, the absence of factor serial correlation, and negligible cross-sectional industry mean return dispersion implies that the serial correlation in industry return components is greater than zero. Grinblatt and Moskowitz go on to further test their results using various techniques, and find the following:

- Industry portfolios exhibit significant momentum, even after controlling for size, book-to-market equity (BE/ME), individual stock momentum, the cross-sectional dispersion in mean returns and potential microstructure influences.
- Once returns are adjusted for industry effects, momentum profits from individual equities are significantly weaker and, for the most part, are statistically insignificant.
- Industry momentum strategies are more profitable than individual stock momentum strategies.
- Industry momentum strategies are robust to various specifications and methodologies (including return scrambling), and they appear to be profitable even among the largest, most liquid stocks.
- Profitability of industry strategies over intermediate horizons is predominantly driven by the long positions. By contrast, the profitability of individual stock momentum strategies is largely driven by selling past losers, particularly among the less liquid stocks.
- Unlike individual momentum, industry momentum is strongest in the short term (at the one-month horizon) and then, like individual stock momentum,

tends to dissipate after 12 months, eventually reversing at long horizons. Thus, the signs of the short-term (less than one month) performances of the industry and individual stock momentum strategies are completely opposite, yet the signs of their intermediate and long-term performances are identical.

In their analysis, Grinblatt and Moskowitz note that other industry momentum trading strategies were employed using more industries in the buy and sell portions of the strategy, and claim the results remained largely the same. However, I find that this conclusion is erroneous, and there is in fact a significant difference in the results obtained. The authors note that Grundy and Martin (1999) have argued that industry momentum may be due to lead-lag effects that are not due to firm size, and point out that this idea is almost tautological. If, indeed, individual stock momentum does not exist intra-industry, industry momentum has to be a lead-lag effect between stocks within the industry. Another important finding of Grinblatt and Moskowitz (1999) is that neither the winners nor the losers portfolio seems to be dominated by a particular industry, and that there appears to be little relation between the sample mean returns of the industries and the frequency with which they appear in the winners' and losers' categories. However, I will show that some industries are featured much more frequently than other industries in the winner and loser portfolios, but that these industries appear frequently in both the winners and losers portfolios. The authors also find that restricting securities to the smallest 20 percent of stocks within each industry substantially increases the profits to the trading strategy, but that this is probably due to a lead-lag effect rather than a size premium. They note that if behavioural patterns generate the profitability of momentum trading strategies, then these strategies must at least be constrained by factor risk exposure that cannot be eliminated. Such factor risk would limit the size of the positions that rational investors would be willing to take. They argue that because industry momentum drives much of individual stock momentum, and stocks within an industry tend to be much more highly correlated than stocks across industries, momentum strategies are not very well diversified. Thus, momentum may be a 'good deal' but is far from an arbitrage. For an explanation of the source of industry momentum, Grinblatt and Moskowitz note the Hong and Stein (1999) suggestion that slow information diffusion into prices causes an initial underreaction to news, but the presence of 'momentum traders' seeking to exploit the slow price movement causes subsequent reversals. In subsequent empirical work, Hong, Lim and Stein (2000) find that momentum is stronger among small firms with low analyst coverage, which they suggest is a proxy for firms with slow information diffusion. Also, it may take time for news to disseminate among firms in an industry. Industry leaders (generally larger, more followed firms) might be the first to receive a piece of information, but this information may slowly diffuse to other firms within the industry as analysts and investors interpret the potential impact of the signal for the industry as a whole. This could create the kind of lead-lag effects among industry leaders and other firms within the industry (that are unrelated to microstructure or delayed common factor responses) that may be generating momentum. Also, Berk, Green and Naik (1999) demonstrate that changes in a firm's growth options that are related to its systematic risk can generate momentum in its returns. Since growth opportunities are likely more correlated among firms within industries versus across industries, and likely depend on industry-specific attributes, it is conceivable that their model would generate industry momentum.

Hong, Lim and Stein (2000) look for evidence that momentum reflects the gradual diffusion of firm-specific information, similar to Chan, Jegadeesh and Lakonishok (1996). They posit that stocks with slower information diffusion should exhibit more pronounced momentum. They note that, for example, it seems plausible that information about small firms gets out more slowly if investors face fixed costs of information acquisition, and hence choose in aggregate to devote more effort to learning about those stocks in which they can take large positions. They admit that firm size is likely to capture other factors as well, potentially confounding their inferences. As an alternative proxy for the rate of information flow, they consider analyst coverage. They posit that stocks with lower analyst coverage should, all else equal, be ones where firm-specific information moves more slowly across the investing public. So, they check whether momentum strategies work better in low-analyst-coverage stocks. Again, they admit that analyst coverage is very strongly correlated with firm size, so they control for the influence of size on analyst coverage by sorting stocks into groups according to their residual analyst coverage, where the residual comes from a regression of coverage on firm size. They find that, with respect to size, once one moves past the very smallest capitalization stocks (where thin market making capacity appears to be an issue) the profitability of momentum strategies declines sharply with market capitalization. Also, holding size fixed, momentum strategies work particularly well among stocks that have low analyst coverage. Further, the marginal importance of analyst coverage is greatest among small stocks. These effects are of a statistically and economically significant magnitude. Momentum profits are roughly 60% greater among the one-third of the stocks with the lowest residual coverage, as compared to the one-third with the highest residual coverage. The effect of analyst coverage is also more pronounced for stocks that are past losers than for stocks that are past winners, i.e. low-coverage stocks seem to react more sluggishly to bad news than to good news. To explain, they use the example of a firm that has no analyst coverage but is sitting on good news. To the extent that its managers prefer higher to lower stock prices, they will push the news out the door themselves, via increased disclosures, etc. On the other hand, if the same firm is sitting on bad news, its managers will have much less incentive to bring investors up to date quickly. Thus the marginal contribution of outside analysts in getting the news out is likely to be greater when the news is bad.

Chan, Hameed and Tong (2000) extend the analysis of momentum strategies to the global equity markets (similar to Rouwenhorst, 1998). They implement the momentum strategies based on individual stock market indices. Second, they examine how the profitability of international momentum strategies is affected by exchange rate movements. Third, they investigate whether trading volume information affects the profitability of momentum strategies. Their results indicate evidence of momentum profits that are statistically and economically significant, especially for short holding periods (less than four weeks). The major source of momentum profits arises from price continuations in individual stock indices. Evidence also indicates that the momentum profits cannot be completely explained by nonsynchronous trading and are not confined to emerging markets, although it seems that they diminish significantly after adjusting for beta risk. When they implement the momentum strategies on markets that experience increases in volume in the previous period, the momentum profits are higher. This indicates that return continuation is stronger following an increase in trading volume.

Grundy and Martin (2001) investigate both the risks and the possible sources of the reward to a short-term momentum strategy which is long prior winners and short prior losers. They show that the strategy's average profitability cannot be explained as a reward for bearing dynamic exposure to the three factors of the Fama and French (1996) model, nor by cross-sectional variability in stocks' average returns, nor by exposure to industry factors. They claim that the strategy's profitability reflects momentum in the stock-specific components of returns. They document that although the returns to an industry-based momentum strategy are consistent with an intra-industry lead-lag effect, industry momentum alone does not explain the profitability of momentum trading strategies. Further, they model and document in a multifactor setting the natural and significant correlation between a momentum strategy's factor loadings and the factor realizations during the period in which stocks were ranked as relative winners versus losers. These dynamic factor loadings induce variability in the strategy's returns that can obscure its profitability. When risk adjusted, the strategy's profitability is remarkably stable across subperiods - even in the pre-1945 period when the strategy's mean raw return is negative. To address Conrad and Kaul's assertion that a momentum strategy's average profitability simply reflects cross-sectional variability in average returns, Grundy and Martin subtract each stock's mean return from its return during the investment period, and find that the momentum strategy's mean return remains statistically and economically significant. The authors note that to the extent that the profitability of a momentum strategy reflects momentum in a component of returns beyond that associated with exposure to the Fama-French factors, a traditional momentum strategy that defines winners and losers in terms of their relative *total* returns is suboptimal. Comparing the profitability of a strategy that defines winners and losers in terms of their relative *stock-specific* (Fama-French factors adjusted) returns to the profitability of a strategy that takes long/short positions in stocks that are winners/losers on a *total* return basis but are not also winners/losers on a *stock-specific* basis, Grundy and Martin find the *stock-specific* return strategy is significantly more profitable than the *total* return strategy, earning a statistically and economically significant risk-adjusted return of more than 1.3% per month over the August 1926-July 1995 period (a similar finding was noted in Rouwenhorst, 1998). This is mainly due to 'hedging out' the reversal of small stocks in the month of January.

Using data over the 1990 to 1997 sample period, Jegadeesh and Titman (2001) find that momentum strategies continue to be profitable and the past winners outperform past losers by about the same magnitude as in the earlier period (discussed in Jegadeesh and Titman, 1993). In addition, the January seasonality is also observed in the more recent sample period. The authors note that the behavioural models attempting to explain momentum specify that holding period returns arise because of a delayed overreaction to information that push the prices of winners (losers) above (below) their long-term values. These models predict that the returns of losers should exceed the returns of winners subsequent to the holding period. In contrast, Conrad and Kaul (1998) suggest that the higher returns of winners in the holding period represent their unconditional expected rates of return and thus predict that the post-formation returns of the momentum portfolio will be positive on average in any post-ranking period. To test the conflicting implications of these theories, Jegadeesh and Titman examine the long-term returns of the winner and loser stocks in the momentum portfolio. Specifically, they examine the returns in each of the 60 months following the portfolio formation date. They find that over the entire sample period of 1965 to 1997, the cumulative return in months 13 to 60 for the momentum portfolio is negative. They note that this finding supports the behavioural models but clearly rejects the Conrad and Kaul (1998) hypothesis which suggests that the winners will continue to outperform the losers outside the momentum strategy holding period. The authors caution that while they find strong evidence of return reversals in the fourth and fifth years following portfolio formation in the 1965 to 1981 time period, they find weak evidence of return reversals in the1982 to 1997 time period, even though the momentum profits are of the same magnitude and significance in both periods. In addition, using an improved version of the Conrad and Kaul return-scrambling technique to randomly scramble the sequence of each stock's returns, Jegadeesh and Titman find that very little, if any, of the momentum profits are due to the cross-sectional variation in mean returns (contrary to Conrad and Kaul, 1998). They therefore conclude that momentum profits observed in the actual data are generated because of the time-series of stock returns, not because of the cross-sectional variation in returns.

Jegadeesh and Titman (2002) present a direct test of the Conrad and Kaul (1998) hypothesis that momentum profits are due to cross-sectional differences in unconditional expected returns. Their results indicate that differences in unconditional expected returns explain very little, if any, of the momentum profits. They show that the difference between the Conrad and Kaul results and their results is due to small sample biases in the Conrad and Kaul empirical tests. They note that Conrad and Kaul's experiments seemingly suggest that the magnitude of momentum profits found in the actual data can be obtained with randomly generated data constructed to have no time-series dependence. However, Jegadeesh and Titman show that Conrad and Kaul's bootstrap experiment and their simulations contain a small sample bias that is identical to the bias in their empirical tests. They present a variation of the Conrad and Kaul bootstrap that they analytically show is unbiased, in which they find that momentum profits are virtually zero. They attribute the Conrad and Kaul results entirely to small sample bias. Intuitively, we know that a stock's realized return over any six-month period provides very little information about the stock's unconditional expected return. Further, the Grinblatt and Moskowitz (1999) finding that there appears to be little relation between the sample mean returns of the industries and the frequency with which they appear in the winners' and losers' categories implies that the cross-sectional differences in unconditional expected returns do not account for the profitability of momentum strategies. I will also show that the industries featured most frequently in the winner portfolios are often the industries featured most frequently in the loser portfolios (similar to Cao and Wei, 2002), which casts further doubt on the importance of the cross-sectional differences in unconditional expected returns.

Cao and Wei (2002) examine return momentums among the fourteen sectors of Canada's TSE 300 Index for the period from January 1961 to December 1999. Their methodology is slightly different from the Jegadeesh and Titman (1993) methodology: the weight of a winner/loser sector (above-average/below-average sector) is determined by the difference between its performance over the ranking period and the performance of an equal-weighted index over the ranking period. In other words, ever sector is represented to some extent in their holding period portfolios (assuming the sector's return was not exactly equal to the average return for the ranking period), with extreme winners/losers having more representation than others. Cao and Wei find a statistically significant return of 0.69 percent per month for the 6-month rank/6-month hold strategy, and statistically significant returns as high as 1.05 percent per month for the 12-month rank/1-month hold strategy. The magnitude of these returns is surprising given that Cao and Wei examine only fourteen sectors. The authors run another version of the strategy which purchases/sells only the top winner and bottom loser portfolios, and obtain even-more significant results. The 6-month/6-month strategy now returns a statistically significant 1.32 percent per month, while the 12-month/1-month strategy now returns a statistically significant 1.59 percent per month. This finding is contrary to the Grinblatt and Moskowitz (1999) finding that the results weren't affected when more industries were employed in the buy and sell portfolios. Cao and Wei find that there is a significant difference between the number of times the most-frequent-winner industry and least-frequent-winner industry appear in the winner portfolio, and the same for the loser portfolio. However, the same industries dominate both the winner and loser portfolios, and a correlation coefficient indicates that a sector is equally likely to be in the extreme winner and loser portfolios. They note that momentum returns are largely driven by sectors with large return variations. They also find that the overall level of standard deviations (across all sectors) determines the overall profitability of the momentum strategy. Continuing, the authors find that the betas for strategies that produce significant positive returns range from -0.008 to 0.164, many of which are not statistically significant. The results collectively suggest that for most of the profitable momentum portfolios, systematic risk is either zero of closer to zero, and so infer that very little systematic risk is borne for the returns earned from momentum strategies. Further, the authors note that a momentum trading strategy can be very profitable, even after accounting for transactions costs and management expenses.

This paper is organized as follows. Section 2 describes the data and methodology used. Section 3 discusses the results of the trading strategies and observations made on the winner and loser portfolios. Section 4 recaps the results, discusses some interesting observations that are not directly related to the study, and concludes on the implications of the study's findings.

2 DATA AND METHODOLOGY

Monthly return data for the period January 1963 to December 2003 for twelve, seventeen and thirty industry groups was obtained from Kenneth French's website.[3] Kenneth assigns each NYSE, AMEX, and NASDAQ stock to an industry portfolio at the end of June of year t based on its four-digit SIC code at that time. He then computes monthly returns from July of t to June of t+1. Stocks are value weighted within industry groups. The data is used to replicate and extend the Grinblatt and Moskowitz (1999) study for the three industry data sets. The methodology is as follows:

1. Industries are ranked and sorted on their J-month returns;
2. Various strategies are employed which purchase the top-performing H portfolios and sell the worst-performing H portfolios;
3. The holding portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1;
4. Portfolios are held for K months and the strategy is repeated monthly.
5. All portfolios are rebalanced monthly to equal weights so that no portfolio has a higher weight in the trading strategy's total holdings than any other portfolio.

This methodology forms zero-cost portfolios, i.e. portfolios whose long position is funded by an equal-value short position. All returns for zero-cost portfolios are reported per dollar long. I also examine the returns for the winner and loser portfolios

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

individually. Returns for all trading strategies are for the period January 1964 to December 2003. Some of the trading strategies require data prior to January 1964 so that the holding period can begin in January 2004. For example, the J=12, K=12 trading strategy requires data from January 1963 (12 months prior to the first holding period) to rank industries on their past 12-month return so that it can begin its first holding period in January 1964. An F-test for the cross-sectional dispersion in mean returns in any of the industry data sets cannot be rejected, thereby implying that the cross-sectional dispersion in mean returns across industries is insignificant for all industry data sets.

3 ANALYSIS OF RESULTS AND OTHER OBSERVATIONS

3.1 Results for zero-cost portfolios

Average monthly returns to various zero-cost (winner-loser) momentum trading strategies employing a 6-month lag period and 12-month lag period for the three industry data sets are shown in Table I and Table II respectively. The following discussion will refer to Table I unless otherwise noted. Recall that Grinblatt and Moskowitz (1999) examine data for 20 industries with the same methodology. For the period July 1963 to July 1995, they find an average monthly return of 0.43 percent for the J=6/K=6 month strategy that purchases the 3 (15.0%) highest-returning industries and sells the 3 (15.0%) lowest-returning industries. My most comparable trading strategy uses 17 industries and purchases the 3 (17.6%) highest-returning industries while selling the 3 (17.6%) lowest-returning industries, and obtains an average monthly return of 0.33 percent for the same time period.[4] This significant difference is not explained by the following two differences (which are the only differences) between the Grinblatt and Moskowitz industry groups and the Kenneth French industry groups:

1. Grinblatt and Moskowitz form their industry groups every month, while Kenneth French forms his industry groups once a year; and
2. Grinblatt and Moskowitz assign stocks to industry groups based on their two-digits SIC codes, while Kenneth French assigns stocks to industry groups based on their four-digit SIC codes.

[4] The results in Table I are for the January 1964 to December 2003 time period. The exact same result was obtained for the J=6/K=6 strategy with 17 industry groups that purchased/sold the top/bottom 3 industries for the January 1964 to July 1995 time period (the Grinblatt and Moskowitz (1999) time period).

Table 1

Average Monthly Returns to Momentum Trading Strategies (1964 - 2003)
Winner - Loser (Zero-Cost) Portfolios, 6-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased while the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and t-statistics are presented in this table. Also, F-Statistics for result differences between the strategy that purchases the highest number of industries and the strategy that purchases the lowest number of industries are presented. A *in dicates that a t-statistic is significant at the 5% level without Bonferroni's adjustment. None of the F-statistics are significant at the 5% level.

12 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
1 (8.3%)	0.49	0.27	0.38	0.44	0.38	1.76	1.10	1.79	2.3*	2.18*
2 (16.7%)	0.47	0.22	0.32	0.38	0.31	2.27*	1.16	1.90	2.58*	2.35*
4 (33.3%)	0.27	0.11	0.15	0.21	0.18	1.88	0.87	1.31	2.06*	1.91
						F-Statistic, 4-1				
						0.49	0.34	0.91	1.13	1.02

17 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
2 (11.8%)	0.33	0.21	0.35	0.49	0.40	1.44	1.00	1.91	3.05*	2.62*
3 (17.6%)	0.37	0.23	0.33	0.44	0.35	1.88	1.32	2.08*	3.07*	2.63*
5 (29.4%)	0.31	0.15	0.22	0.32	0.26	2.09*	1.09	1.82	2.83*	2.54*
						F-Statistic, 5-2				
						0.01	0.06	0.35	0.75	0.58

30 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
3 (10.0%)	0.83	0.68	0.66	0.74	0.59	3.33*	2.97*	3.20*	3.97*	3.39*
6 (20.0%)	0.66	0.49	0.51	0.55	0.44	3.57*	2.88*	3.29*	3.93*	3.36*
9 (30.0%)	0.54	0.37	0.37	0.41	0.34	3.63*	2.67*	2.97*	3.63*	3.23*
						F-Statistic, 9-3				
						0.99	1.34	1.45	2.29	1.51

Table 2

Average Monthly Returns to Momentum Trading Strategies (1964 - 2003)
Winner - Loser (Zero-Cost) Portfolios, 12-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased while the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and t-statistics are presented in this table. Also, F-Statistics for result differences between the strategy that purchases the highest number of industries and the strategy that purchases the lowest number of industries are presented. A *in dicates that a t-statistic is significant at the 5% level without Bonferroni's adjustment. None of the F-statistics are significant at the 5% level.

12 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	**12/1**	**12/3**	**12/6**	**12/9**	**12/12**	**12/1**	**12/3**	**12/6**	**12/9**	**12/12**
	Average Monthly Return (%)					t-Statistic				
1 (8.3%)	0.62	0.48	0.39	0.29	0.23	2.13*	1.80	1.60	1.27	1.07
2 (16.7%)	0.68	0.51	0.41	0.36	0.28	3.23*	2.54*	2.22*	2.04*	1.66
4 (33.3%)	0.43	0.35	0.28	0.24	0.17	3.01*	2.60*	2.21*	2.02*	1.52
						F-Statistic, 4-1				
						0.34	0.19	0.16	0.04	0.06

17 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	**12/1**	**12/3**	**12/6**	**12/9**	**12/12**	**12/1**	**12/3**	**12/6**	**12/9**	**12/12**
	Average Monthly Return (%)					t-Statistic				
2 (11.8%)	0.72	0.60	0.54	0.47	0.36	3.19*	2.82*	2.61*	2.33*	1.85
3 (17.6%)	0.61	0.55	0.44	0.38	0.29	3.07*	2.91*	2.47*	2.22*	1.78
5 (29.4%)	0.59	0.47	0.38	0.31	0.24	3.78*	3.17*	2.74*	2.32*	1.90
						F-Statistic, 5-2				
						0.22	0.25	0.41	0.44	0.27

30 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	**12/1**	**12/3**	**12/6**	**12/9**	**12/12**	**12/1**	**12/3**	**12/6**	**12/9**	**12/12**
	Average Monthly Return (%)					t-Statistic				
3 (10.0%)	0.97	0.88	0.74	0.61	0.45	3.65*	3.53*	3.25*	2.79*	2.18*
6 (20.0%)	0.86	0.73	0.58	0.46	0.33	4.41*	3.94*	3.33*	2.79*	2.11*
9 (30.0%)	0.76	0.57	0.46	0.37	0.25	4.83*	3.79*	3.24*	2.72*	1.95
						F-Statistic, 9-3				
						0.46	1.13	1.09	0.87	0.68

Given this information, it is difficult to understand why there is a significant difference in the Grinblatt and Moskowitz average monthly return and my average monthly return over the same time period. However, it's possible that there is a significant difference between dividing stocks into 17 industries and dividing stocks into 20 industries. For example, dividing stocks into 17 industries might dilute momentum profits by combining a high-momentum 'sub-group' of stocks with another, not-so-high-momentum 'sub-group' of stocks; this combined group might have been separated if we were dividing into 20 industries instead. This idea is supported by the fact that the J=6/K=6 strategy for 30 industry groups that purchases the 6 (20.0%) highest-returning industries and sells the 6 (20.0%) lowest-returning industries for the same time period has an average monthly return of 0.51 percent, significantly higher than the corresponding Grinblatt and Moskowitz finding of 0.43 percent for 20 industries.

The first major observation is that momentum profits increase significantly when fewer industries are purchased and sold. For example, the average difference (across 6-month lag strategies) in average monthly profits between the 30-industry strategy that purchases/sells the top/bottom 3 industries and the 30-industriy strategy that purchases/sells the top/bottom 9 industries amounts to 3.75 percent per month annualized. This is a significant incremental annual return by most standards. This difference is also present in the 17-industry and 12-industry data sets, with a 1.29 percent per month annualized average difference for the 17-industry data set and a 2.58 percent per month annualized average difference for the 12-industry data set. However, we cannot reject any of the F-tests for differences in the means of the trading strategies that purchase the highest number of industries and the trading strategies that purchase the lowest number of industries for any of three industry data sets. Nevertheless, there is a clear pattern exhibited in all three industry data sets except for the J=6/K=1, J=6/K=3 and J=6/K=6 strategies in the 17-industry data set. The higher returns observed for purchasing/selling fewer industries intuitively make sense if we consider that we take on more risk by purchasing and selling fewer industries. By purchasing and selling fewer industries, we are less diversified across industries and are more exposed to industry-specific factors, thereby making the portfolio more vulnerable to a downturn in a particular industry group that we hold.

Another interesting observation is that momentum profits for equivalent strategies are higher when we include more industries in the universe. That is, the strategy that includes 30 industries in the universe and purchases/sells the top/bottom 9 (30.0% of) industries is significantly more profitable than the equivalent strategy that includes 12 industries in the universe and purchases/sells the top/bottom 4 (33.3% of) industries. This amounts to a statistically significant difference between these two strategies of 3.28 percent per month annualized (t-statistic = 2.99). Overall, the average difference (across the 6-month lag strategies and across the number of industries purchased and sold) in average monthly profits between the 30-industry data set and the 12-industry data set amounts to 2.92 percent per month annualized. Again, this is a significant incremental annual return by most standards. We also observe that all the t-statistics for the 30-industry data set are significant at the 1% level, whereas only six t-statistics for the 12-industry data set are significant at the 5% level (without the Bonferroni adjustment).[5] This finding makes intuitive sense; we would expect the opportunity for momentum profits to increase as we increased

[5] The Bonferroni adjustment adjusts the critical values for t-statistics upwards for studies that run multiple tests over the same data set. It is generally accepted that we should expect higher t-statistics in such a study, but there is considerable uncertainty about the appropriate magnitude of the adjustment. I choose not to use the Bonferroni adjustment because it is controversial and is very conservative. However, we should expect slightly higher t-statistics when running multiple comparable strategies using the same data set.

the number of industries in the universe. Increasing the number of industries gives more of a chance for extreme-returning sub-groups of stocks to be represented in the return for any given industry, i.e. less chance of dilution of the returns of these extreme-returning sub-groups by having them grouped with other, average-returning sub-groups. While stocks within industry groups are valued-weighted, some industries will still have a lower average market capitalization than other industries, especially in the 30-industry data set. This could increase the chance for a small-cap effect on the results of the 30-industry data set, in which case we would expect higher returns to the trading strategies. Even so, this finding is inconsistent with the Grinblatt and Moskowitz conclusion that industries account for almost all of the momentum profits observed in individual stocks. If this were true, we would expect the returns to momentum trading strategies to remain the same when we varied the number of industries in the universe. Indeed, it is almost tautological that profits to momentum trading strategies would decrease as we decreased the number of industries in the universe. For example, imagine the profits to momentum strategies in a two-industry universe. The return-dilution effect within industries would eliminate any opportunity for momentum profits. While it is clear that Grinblatt and Moskowitz have found a significant relation between momentum profits and industry groups, industry groups can not account for all of the profits to momentum trading strategies. This finding begs the question, "what level of industry breakdown best captures the economic differences between industries?"

3.2 Results for winner and loser portfolios

Average monthly returns to various winner momentum trading strategies employing a 6-month lag period and 12-month lag period for the three industry data sets are shown in Table III and Table IV respectively.

Table 3

Average Monthly Returns to Momentum Trading Strategies (1964 - 2003)
Winner Portfolios, 6-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and t-statistics are presented in this table. The Bonferroni adjusted t-stat is 3.36 at the 5% level and 3.79 at the 1% level. All t-statistics are significant at the 1% level.

12 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
1 (8.3%)	1.19	1.22	1.33	1.30	1.23	4.77	5.10	5.69	5.66	5.39
2 (16.7%)	1.23	1.14	1.22	1.22	1.15	5.69	5.30	5.70	5.76	5.49
4 (33.3%)	1.12	1.07	1.10	1.12	1.09	5.43	5.27	5.43	5.55	5.45

17 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
2 (11.8%)	1.17	1.16	1.25	1.28	1.21	4.80	5.00	5.49	5.70	5.45
3 (17.6%)	1.21	1.17	1.23	1.25	1.19	5.24	5.18	5.54	5.68	5.47
5 (29.4%)	1.17	1.09	1.13	1.17	1.14	5.46	5.09	5.30	5.49	5.39

30 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
3 (10.0%)	1.58	1.47	1.50	1.51	1.41	6.20	5.93	6.14	6.24	5.91
6 (20.0%)	1.35	1.29	1.31	1.33	1.27	5.87	5.69	5.84	5.90	5.68
9 (30.0%)	1.31	1.24	1.25	1.26	1.22	6.02	5.70	5.72	5.74	5.60

Table 4

Average Monthly Returns to Momentum Trading Strategies (1964 - 2003)
Winner Portfolios, 12-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and t-statistics are presented in this table. The Bonferroni adjusted t-stat is 3.36 at the 5% level and 3.79 at the 1% level. All t-statistics are significant at the 1% level.

12 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	12/1	12/3	12/6	12/9	12/12	12/1	12/3	12/6	12/9	12/12
	Average Monthly Return (%)					t-Statistic				
1 (8.3%)	1.41	1.28	1.18	1.08	1.05	5.52	5.09	4.76	4.37	4.27
2 (16.7%)	1.38	1.31	1.22	1.16	1.12	6.09	5.83	5.54	5.22	5.04
4 (33.3%)	1.23	1.18	1.14	1.13	1.09	5.84	5.65	5.53	5.42	5.26

17 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	12/1	12/3	12/6	12/9	12/12	12/1	12/3	12/6	12/9	12/12
	Average Monthly Return (%)					t-Statistic				
2 (11.8%)	1.44	1.40	1.28	1.23	1.17	5.90	5.87	5.43	5.21	4.94
3 (17.6%)	1.31	1.29	1.21	1.17	1.13	5.59	5.56	5.30	5.16	5.02
5 (29.4%)	1.29	1.22	1.18	1.15	1.11	5.82	5.54	5.41	5.30	5.15

30 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	12/1	12/3	12/6	12/9	12/12	12/1	12/3	12/6	12/9	12/12
	Average Monthly Return (%)					t-Statistic				
3 (10.0%)	1.57	1.59	1.49	1.39	1.30	6.00	6.11	5.81	5.50	5.16
6 (20.0%)	1.50	1.41	1.34	1.28	1.22	6.42	6.04	5.71	5.48	5.23
9 (30.0%)	1.46	1.34	1.28	1.24	1.19	6.46	5.92	5.68	5.52	5.28

The following discussion will refer to Table III unless otherwise noted. The results show that the patterns that were observed for the zero-cost trading strategies also exist for the winner portfolios independently (as would be expected). Other than a few exceptions, profits increase as fewer industries are purchased and sold. Also, trading strategies using the 30-industry data set are much more profitable than the 17-

industry and 12-industry strategies. The average monthly return for the 30-industry data set is 17.46% annualized, while the average monthly returns for the 17-industry and 12-industry data sets are 15.25% and 15.12% respectively. Worth noting here are the abnormal profits obtainable from the winner portfolios. The buy and hold, industry equal-weighting (rebalanced monthly) average monthly returns for the 12-industry, 17-industry and 30 industry data sets are 1.00%, 1.00% and 1.05% respectively. These returns can be thought of as the passive buy and hold returns, or index returns, for the various industry data sets. For purposes of this discussion, I define the abnormal return to a trading strategy as the return above the corresponding passive buy and hold return. The J=6/K=1 trading strategy that purchases/sells the top/bottom 3 industries in the 30-industry universe has an abnormal average monthly return of 6.6% annualized, while the equivalent strategy that purchases/sells the top/bottom 9 industries has an abnormal average monthly return of 3.2% annualized. Collectively, the J=6 trading strategies in the 30-industry data set have an average abnormal monthly return of 3.66% annualized, while the equivalent trading strategies in the 17-industry and 12-industry data sets have abnormal average monthly returns of 2.30% and 2.18% annualized respectively.

Average monthly returns to various loser momentum trading strategies employing a 6-month lag period and 12-month lag period for the three industry data sets are shown in Table V and Table VI respectively.

Table 5

Average Monthly Returns to Momentum Trading Strategies (1964 - 2003)
Loser Portfolios, 6-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and t-statistics are presented in this table. The Bonferroni adjusted t-stat is 3.36 at the 5% level and 3.79 at the 1% level.

12 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
1 (8.3%)	0.70	0.95	0.95	0.86	0.85	2.71	3.92	4.18	3.95	4.04
2 (16.7%)	0.76	0.92	0.90	0.84	0.84	3.12	3.97	4.04	3.94	4.02
4 (33.3%)	0.85	0.96	0.95	0.91	0.91	3.94	4.53	4.54	4.43	4.50

17 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
2 (11.8%)	0.84	0.95	0.90	0.78	0.80	3.17	3.76	3.74	3.34	3.47
3 (17.6%)	0.84	0.93	0.90	0.81	0.84	3.37	3.90	3.92	3.58	3.73
5 (29.4%)	0.86	0.94	0.91	0.85	0.88	3.68	4.16	4.10	3.90	4.03

30 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	6/1	6/3	6/6	6/9	6/12	6/1	6/3	6/6	6/9	6/12
	Average Monthly Return (%)					t-Statistic				
3 (10.0%)	0.75	0.79	0.85	0.77	0.83	2.70	2.99	3.35	3.16	3.44
6 (20.0%)	0.69	0.79	0.80	0.78	0.83	2.74	3.21	3.38	3.35	3.60
9 (30.0%)	0.77	0.87	0.88	0.84	0.88	3.20	3.67	3.82	3.74	3.92

Table 6

Average Monthly Returns to Momentum Trading Strategies (1964 - 2003)
Loser Portfolios, 12-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and t-statistics are presented in this table. The Bonferroni adjusted t-stat is 3.36 at the 5% level and 3.79 at the 1% level.

12 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	12/1	12/3	12/6	12/9	12/12	12/1	12/3	12/6	12/9	12/12
	Average Monthly Return (%)					t-Statistic				
1 (8.3%)	0.80	0.80	0.79	0.79	0.81	3.00	3.14	3.27	3.40	3.59
2 (16.7%)	0.70	0.80	0.81	0.80	0.84	2.99	3.44	3.61	3.64	3.88
4 (33.3%)	0.80	0.83	0.87	0.88	0.92	3.75	3.94	4.15	4.27	4.46

17 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	12/1	12/3	12/6	12/9	12/12	12/1	12/3	12/6	12/9	12/12
	Average Monthly Return (%)					t-Statistic				
2 (11.8%)	0.73	0.80	0.74	0.76	0.81	2.80	3.18	3.02	3.13	3.39
3 (17.6%)	0.70	0.74	0.77	0.79	0.85	2.80	3.04	3.24	3.35	3.64
5 (29.4%)	0.69	0.75	0.80	0.84	0.87	2.96	3.24	3.50	3.72	3.91

30 Industries Analyzed

	Trading Strategy (J/K)									
# Purchased/Sold	12/1	12/3	12/6	12/9	12/12	12/1	12/3	12/6	12/9	12/12
	Average Monthly Return (%)					t-Statistic				
3 (10.0%)	0.61	0.71	0.75	0.79	0.85	2.21	2.72	2.91	3.08	3.36
6 (20.0%)	0.64	0.68	0.76	0.82	0.89	2.54	2.79	3.17	3.45	3.77
9 (30.0%)	0.70	0.77	0.82	0.88	0.94	2.93	3.25	3.54	3.80	4.11

The following discussion will refer to Table V unless otherwise noted. For this discussion, we have to imagine that we are short the loser portfolios. Therefore, a decrease in profits in Table V is actually an increase in trading strategy profits. The results show that the patterns that were observed for the zero-cost and winner trading strategies do not exist for the loser portfolios independently. Profits do not consistently increase as fewer industries are purchased and sold. We can see that profits often decrease when we move from the strategy that purchases the second-most industries to the strategy that purchases the fewest industries. This seems to imply that extreme-loser industries experience a slowing of their losses in the holding period. We also observe that trading strategies using the 30-industry data set are only slightly more profitable than the 17-industry and 12-industry strategies. The average monthly return across strategies for the 30-industry data set is 10.16% annualized, compared to 10.95% and 11.09% for the 17-industry and 12-industry data sets respectively (remember that since we are short, a lower return is more profitable for us). Recall that the passive average monthly returns for the 12-industry, 17-industry and 30 industry data sets are 1.00%, 1.00% and 1.05% respectively. Using these figures, the J=6 trading strategies in the 30-industry data set have an abnormal average monthly return of 3.19% annualized, while the 17-industry and 12-industry data sets have abnormal average monthly returns of 1.73% annualized and 1.59% annualized respectively. Recalling the abnormal average monthly return figures from the winners, these results indicate that the zero-cost momentum strategies are driven more from the long side than from the short side of the transaction.

3.3 High-momentum industries

Tables VII, VIII and IX present the frequency of industry appearances in the momentum portfolios for the 30-industry, 17-industry and 12-industry strategies respectively. All tables are based on a J=6 strategy.

Table 7

Most Frequent Appearances in Momentum Portfolios (1964 - 2003)
30 Industries Analyzed, 6-Month Lag Period

Panel A: Statistics are shown for the frequency of industry appearaces. The proportion of industry-months occupied by the industries featured in the Max, Min, Mean and Median statistics is displayed in brackets.

Panel B: Industries were ranked from 1 to 3 for the frequency of their appearances in the winner portfolios, losers portfolios, and total appearances in both portfolios. An industry's ranking in total sample period average monthly return is shown in brackets. Industry definitions are available on Kenneth French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Panel A

	Trading Strategy (J = 6)		
Rank	**Hold 3**	**Hold 6**	**Hold 9**
	Winner Appearances		
Max	118 (8.2%)	175 (6.1%)	210 (4.9%)
Min	13 (0.9%)	50 (1.7%)	99 (2.3%)
Mean	48 (3.3%)	96 (3.3%)	144 (3.3%)
Median	48 (3.3%)	103 (3.6%)	147 (3.4%)
	Loser Appearances		
Max	128 (8.9%)	167 (5.8%)	202 (4.7%)
Min	5 (0.4%)	34 (1.2%)	84 (1.9%)
Mean	48 (3.3%)	96 (3.3%)	144 (3.3%)
Median	45 (3.1%)	92 (3.2%)	142 (3.3%)

Panel B

	Most Frequent Total Appearances		
1	Coal (16)	Coal (16)	Coal (16)
2	Mines (21)	Mines (21)	Mines (21)/Telecom (27)
3	Tobacco (1)	Telecom (27)	Tobacco (1)
	Most Frequent Winner Appearances		
1	Tobacco (1)	Tobacco (1)	Tobacco (1)
2	Mines (21)	Telecom (27)	Telecom (27)/Meals (2)
3	Coal (16)	Carry (4)/Coal (16)	Carry (4)
	Most Frequent Loser Appearances		
1	Coal (16)	Coal (16)	Coal (16)
2	Mines (21)	Mines (21)	Mines (21)
3	Telecom (27)	Telecom (27)	Steel (30)

Table 8

Most Frequent Appearances in Momentum Portfolios (1964 - 2003)
17 Industries Analyzed, 6-Month Lag Period

Panel A: Statistics are shown for the frequency of industry appearaces. The proportion of industry months occupied by the industries featured in the Max, Min, Mean and Median statistics is displayed in brackets.
Panel B: Industries were ranked from 1 to 3 for the frequency of their appearances in the winner portfolios, losers portfolios, and total appearances in both portfolios. An industry's ranking in total sample period average monthly return is shown in brackets. Industry definitions are available on Kenneth French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Panel A

	Trading Strategy (J = 6)		
Rank	**Hold 2**	**Hold 3**	**Hold 5**
	Winner Appearances		
Max	91 (9.5%)	123 (8.5%)	178 (7.4%)
Min	12 (1.3%)	27 (1.9%)	72 (3.0%)
Mean	56 (5.8%)	85 (5.9%)	141 (5.9%)
Median	60 (6.3%)	84 (5.8%)	139 (5.8%)
	Loser Appearances		
Max	101 (10.5%)	134 (9.3%)	206 (8.6%)
Min	19 (2.0%)	39 (2.7%)	88 (3.7%)
Mean	56 (5.9%)	85 (5.9%)	141 (5.9%)
Median	49 (5.1%)	72 (5.0%)	132 (5.5%)

Panel B

	Most Frequent Total Appearances		
1	Mines (11)	Mines (11)	Mines (11)
2	Clothes (8)	Clothes (8)	Clothes (8)
3	Utilities (16)	Utilities (16)	Utilities (16)
	Most Frequent Winner Appearances		
1	Mines (11)	Mines (11)	Consumer (1)
2	Consumer (1)	Consumer (1)	Clothes (8)
3	Oil (7)	Oil (7)	Oil (7)
	Most Frequent Loser Appearances		
1	Mines (11)	Mines (11)	Steel (17)
2	Clothes (8)	Steel (17)	Utilities (16)
3	Utilities (16)	Utilities (16)	Mines (11)

Table 9

Most Frequent Appearances in Momentum Portfolios (1964 - 2003)
12 Industries Analyzed, 6-Month Lag Period

Panel A: Statistics are shown for the frequency of industry appearances. The proportion of industry-months occupied by the industries featured in the Max, Min, Mean and Median statistics is displayed in brackets.

Panel B: Industries were ranked from 1 to 3 for the frequency of their appearances in the winner portfolios, losers portfolios, and total appearances in both portfolios. An industry's ranking in total sample period average monthly return is shown in brackets. Industry definitions are available on Kenneth French's website:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Panel A

	Trading Strategy (J = 6)		
Rank	**Hold 1**	**Hold 2**	**Hold 4**
		Winner Appearances	
Max	79 (16.5%)	119 (12.4%)	196 (10.2%)
Min	6 (1.3%)	28 (2.9%)	106 (5.5%)
Mean	40 (8.3%)	80 (8.3%)	160 (8.3%)
Median	38 (7.9%)	86 (8.9%)	160 (8.3%)
		Loser Appearances	
Max	77 (16.0%)	135 (14.1%)	207 (10.8%)
Min	11 (2.3%)	36 (3.8%)	95 (5.0%)
Mean	40 (8.3%)	80 (8.3%)	160 (8.3%)
Median	35 (7.3%)	76 (7.9%)	165 (8.6%)

Panel B

		Most Frequent Total Appearances	
1	Business Equipment (5)	Telecom (11)	Telecom (11)
2	Energy (6)	Business Equipment (5)	Energy (6)
3	Telecom (11)E	nergy (6)	Utilities (12)
		Most Frequent Winner Appearances	
1	Business Equipment (5)	Business Equipment (5)	Health (1)
2	Energy (6)	Telecom (11)	Energy (6)
3	Health (1)	Energy (6)	Telecom (11)
		Most Frequent Loser Appearances	
1	Energy (6)	Telecom (11)	Telecom (11)
2	Business Equipment (5)	Utilities (12)	Utilities (12)
3	Telecom (11)	Business Equipment (5)	Business Equipment (5)

All three tables clearly indicate that some industries appear much more frequently in the momentum portfolios than other industries. This is obviously most pronounced when we purchase/sell the fewest number of industries. For example, for the 12-industry strategy that purchases 1 industry, one of the industries appears 79 times (out of a possible 480) in the winner portfolio while another appears only 6 times. Similarly, for the same strategy, one of the industries appears 77 times (out of a possible 480) in the loser portfolio while another appears only 11 times. The mean number of appearances for all strategies in both the winner and loser portfolios is 1/(# of industries examined). While some industries appear much more frequently than others in the winner and loser portfolios, no one industry dominates either portfolio in any strategy. The data (not displayed) shows that there is a gradual and steady decrease in number of appearances from the most-frequently-featured industry to the least-frequently-featured industry in the winner and loser portfolios for all strategies. The tables also show that the portion of industry-months occupied by any one industry decreases as we allow the purchase/sale of more industries, as would be expected. It's important to note that an industry can only be selected a maximum of 480 times in any strategy (no matter how many industries we allow for purchase/sale), i.e. an industry cannot be selected twice in the same month. Glancing at Panel B in Tables VII, VIII and IX, we notice that the industries that are most frequently selected for the winners portfolio are also most frequently selected for the losers portfolio. Moreover, most of the most-frequently-featured industries are considered cyclical and highly sensitive to the business cycle. For example, in Table IX we see that Business Equipment is featured as a top-three winner or top-three loser 5 out of a possible 6 times. Business Equipment includes computers, software and electronic equipment, all items whose demand is highly sensitive to the business cycle. For another example, in Table VIII we see that Mines is also featured as a top-three winner or top-three loser 5 out of a possible 6 times. Mines includes mining and mineral production, a commodity business that we expect to experience high cyclicality. So, while no one industry dominates the winner and loser portfolios, it appears that industries that are highly sensitive to the business cycle are contributing the most to the performance of both the winner and loser portfolios, and hence to the performance of the zero-cost momentum strategy. However, the fact that the industries that appear most frequently in the winner portfolio also appear most frequently in the loser portfolio is a strong argument against the Conrad and Kaul hypothesis that the profitability of momentum strategies is a function of the cross-sectional dispersion in expected returns. Further, we see that the industries featured most frequently in the winner portfolios are not the industries with the highest average monthly return in the sample (ranks in average monthly return in the sample are shown in brackets in Panel B) . For example, Mines, ranked most-frequently selected industry in the 17-industry winner portfolios 2 out of a possible 3 times, is ranked only 11th in average monthly return over the sample period. A regression of average monthly return in the sample on frequency of winner appearances for the 17-industry strategy that purchases/sells 1 industry returns an r^2 of 11.3% and an insignificant t-statistic on the winner frequency variable. A similar regression of average monthly return in the sample on frequency of loser appearances for the 17-industry strategy that purchases/sells 1 industry returns an r^2 of 16.3% and an insignificant t-statistic on the loser frequency variable. Slightly stronger results are found when we examine strategies that purchase/sell more industries. For example, similar regressions on the 17-industry strategy that purchases/sells 5 industries return an r^2 of 35.7% and t-statistic of 2.9 for the winner appearances and an r^2 of 36.8% and a t-statistic of 3.0 for the loser appearances.

However, these results are hardly an indication that the cross-sectional dispersion in expected returns accounts for the profits to momentum strategies.

3.4 Holding period monthly returns and calendar month returns

Tables X and XI show month-by-month returns in the holding period of the zero-cost momentum strategy for the J=6 and J=12 strategies respectively. The following discussion refers to Table X unless otherwise noted. Notice that returns for all three strategies drop off in month 2 of the holding period. This effect is most pronounced for the 12-industry strategy, where the average monthly return drops from 0.47% in the first month of the holding period to 0.06% in the second month of the holding period. Average monthly returns peak in month 8 of the holding period for the 12-industry and 30-industry strategies, and month 7 of the holding period for the 17-industry strategy. Average monthly returns for all strategies decline steadily and rapidly after the peak month, reaching 0.00% for the 30-industry strategy by holding month 12. In Table XI we can see that average monthly returns peak in month 1 of the holding period and decline slowly and steadily throughout the remainder of the holding period. Profits to the 12-month lag strategies are all negative by holding month 12. The peak in month 1 of the holding period for the 12-month lag period strategy and month 7 of the holding period for the 6-month lag period strategy are equivalent, i.e. a total of 13 months of evaluation + holding has taken place for both strategies by the time these months are finished. However, recall that only one of the 6-month lag strategies peaks in month 7; the others peak in month 8. Note that the 6-month lag strategy has a longer duration of profitability than the 12-month lag strategy. We might expect this because the 12-month strategy has already allowed the industry to outperform its peers for 12 months, allowing more of the profits to be 'used up'

Table 10

Month-by-Month Returns to Momentum Trading Strategy (1964-2003)
6-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased while the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and their respective t-statistics are shown for various months in the holding period.

12 Industries Analyzed, 2 (16.7%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
1	0.47	2.27	7	0.54	2.71
2	0.06	0.29	8	0.55	2.81
3	0.12	0.57	9	0.41	2.11
4	0.32	1.55	10	0.13	0.64
5	0.48	2.47	11	0.11	0.56
6	0.43	2.28	12	0.05	0.28

17 Industries Analyzed, 3 (17.6%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
1	0.37	1.88	7	0.80	4.37
2	0.14	0.71	8	0.74	3.89
3	0.20	1.01	9	0.41	2.28
4	0.27	1.40	10	0.08	0.42
5	0.26	1.47	11	0.16	0.87
6	0.72	3.91	12	0.03	0.14

30 Industries Analyzed, 6 (20.0%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
1	0.66	3.57	7	0.70	3.99
2	0.40	2.15	8	0.73	4.13
3	0.42	2.39	9	0.50	2.86
4	0.46	2.59	10	0.25	1.42
5	0.47	2.84	11	0.10	0.55
6	0.63	3.69	12	0.00	0.00

Table 11

Month-by-Month Returns to Momentum Trading Strategy (1964-2003)
12-Month Lag Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased while the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and their respective t-statistics are shown for various months in the holding period.

12 Industries Analyzed, 2 (16.7%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
1	0.68	3.23	7	0.27	1.34
2	0.43	2.00	8	0.24	1.20
3	0.41	1.91	9	0.19	0.92
4	0.37	1.82	10	0.11	0.55
5	0.23	1.11	11	0.07	0.32
6	0.28	1.40	12	-0.12	-0.62

17 Industries Analyzed, 3 (17.6%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
1	0.61	3.07	7	0.43	2.18
2	0.50	2.53	8	0.16	0.84
3	0.53	2.71	9	0.18	0.93
4	0.31	1.56	10	0.03	0.19
5	0.31	1.61	11	-0.01	-0.05
6	0.35	1.80	12	-0.03	-0.15

30 Industries Analyzed, 6 (20.0%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
1	0.86	4.41	7	0.31	1.72
2	0.68	3.57	8	0.21	1.14
3	0.64	3.41	9	0.18	1.00
4	0.46	2.53	10	0.06	0.36
5	0.40	2.23	11	-0.09	-0.52
6	0.39	2.17	12	-0.16	-1.01

before the holding period begins. While the J=12/K=1 strategy seems to be the most profitable (as is also indicated in Tables I and II), the high turnover of this strategy (100% turnover per month) would probably eliminate the bulk of its profitability. As a combination of high profitability and low turnover, the J=6/K=9 strategy is the best. This strategy requires turning over only 11.1% (1/9) of the portfolio every month, or 133.3% per year, a not-all-too-uncommon turnover for many growth fund managers.

Table XII shows average monthly returns to the J=6/K=6 zero-cost momentum strategy in the calendar months of the year. We can immediately see that there are some significant differences in the results for the three strategies. For example, the 12-industry strategy experiences a large negative return in October, while the 17-industry strategy experiences only a small negative return in the same month and the 30-industry strategy experiences a positive return in the same month. On the other hand, the 12-industry strategy experiences a positive return in July, while the 17-industry strategy experiences a smaller positive return in the same month and the 30-industry strategy experiences a negative return in the same month. There is some evidence for the 'January-effect', or the effect of stocks consistently having negative returns in the month of January (especially small cap stocks), in the tables. All three strategies experience negative returns in January. Moreover, January is the 30-industry strategy's lowest returning month; since this strategy is the one most-affected by small cap stocks, this makes sense. On the other hand, we can see that the 12-industry strategy's negative return in October is more statistically significant than its negative return in January. However, since this study is not focused on the January effect, I will end my speculations here. Most noticeable are the returns in June and December. June and December are the highest returning months for all three strategies. Moreover, these months outpace all other months by a significant

Table 12

Returns to Momentum Trading Strategy Throughout the Calendar Year (1964-2003)
6-Month Lag Period, 6-Month Hold Period

Stocks are assigned to industry groups annually and the return for industry groups is calculated monthly on a value-weighted basis, as obtained from Kenneth French. Industry portfolios are ranked in descending order based on J-month lagged returns, and the top H of industry portfolios (winners) are purchased while the bottom H of industry portfolios (losers) are sold. The portfolios are held for K months and are rebalanced monthly to equal weightings. The portfolios are formed immediately after the lag period, i.e. a portfolio ranked on returns ending on January 30 is formed on February 1. This strategy is repeated monthly for the period January 1964 to December 2003, and the average monthly returns and their respective t-statistics are shown for the months of the calendar year.

12 Industries Analyzed, 2 (16.7%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
Jan	-0.83	-1.04	Jul	0.38	0.79
Feb	1.06	1.50	Aug	-0.02	-0.04
Mar	0.68	1.35	Sep	0.44	0.90
Apr	-0.24	-0.41	Oct	-0.70	-1.11
May	0.24	0.47	Nov	0.44	0.72
Jun	1.10	2.58	Dec	1.26	2.27

17 Industries Analyzed, 3 (17.6%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
Jan	-0.50	-0.75	Jul	0.17	0.32
Feb	0.66	1.00	Aug	-0.24	-0.47
Mar	0.12	0.25	Sep	0.30	0.60
Apr	-0.48	-0.84	Oct	-0.29	-0.51
May	0.53	1.39	Nov	0.89	1.86
Jun	1.36	2.66	Dec	1.41	2.45

30 Industries Analyzed, 6 (20.0%) Purchased/Sold

Month	Avg Return (%)	t-stat	Month	Avg Return (%)	t-stat
Jan	-0.56	-0.81	Jul	-0.03	-0.06
Feb	0.78	1.20	Aug	-0.29	-0.62
Mar	0.79	1.72	Sep	0.55	1.31
Apr	0.14	0.23	Oct	0.35	0.68
May	0.43	0.87	Nov	1.08	2.00
Jun	1.40	2.94	Dec	1.46	2.87

margin for the 17-industry and 30-industry strategies and have the most statistically significant returns (the 12-industry strategy also has a very high return in February, albeit much less statistically significant than its June and December returns). The June and December returns account for 46.9%, 70.5% and 61.9% of the total return available throughout the calendar year for the 30-industry, 17-industry and 12-industry strategies respectively. This is especially noteworthy when we consider that June and December are the most statistically significant months for all strategies by a considerable margin.

3.5 Momentum performance in bull and bear markets

Tables 13 and 14 show statistics on the performance of a J=6/K=6, 30-industry zero-cost strategy with 6 industries purchased/sold during bull and bear markets in the 1964 to 2003 time period. Table 13 shows results versus the 'buy-and-hold' passive strategy of buying all industries and rebalancing to equal weights every month, while Table 14 shows results versus buying and holding the CRSP Value-Weighted Index. The results in both tables are striking. The following discussion will refer to Table 13 unless otherwise noted, as Table 13 is the more conservative analysis. While it has already been found that zero-cost momentum strategies have virtually no factor risk (as measured by the CAPM beta or by the Fama-French three-factor model betas), these results indicate that momentum strategies outperform in bear markets and underperform in bull markets. In fact, the only exception to this is during the bull market of October 1998 to March 2000, also known as the tech bubble. During this period, winners significantly outperformed and losers significantly underperformed to give the momentum strategy 2.1 times the market's average monthly return. Amazingly, the zero-cost momentum strategy went on to outperform the market in the subsequent bear market of April 2000 to September 2002, driven entirely by the underperformance of the loser portfolio. We can see that the zero-cost momentum strategy is incredibly resilient in time of market crisis. For example, the zero-cost momentum strategy returned an average -0.03% per month in the crash of 1987 (September 1987 to November 1987 inclusive), vs. the market return of -11.12% per month. This makes intuitive sense; the notion of a 'flight to quality' in times of market crisis means that managers would quickly buy up stocks they perceive as safe and dump stocks they perceive as risky. The quick rise in the prices of the safe stocks would create high momentum for these stocks, and they would thus be included in the momentum winners portfolio in the second month of the crisis (the return for these stocks in the first month of the crisis would likely be so high as to have a significant impact on their six-month past performance). These stocks would likely continue their momentum throughout the crisis as managers continue to shuffle their portfolios into safe stocks and away from risky stocks. The quick fall in the price of the risky stocks would create the opposite effect for these stocks, and they would thus be included in the momentum losers portfolio in the second month of the crisis. In effect, the zero-cost momentum strategy is a 'quick-response mechanism' to market price signals in a market crisis. We also see this pattern in the minor crises of August 1990 to October 1990 and August 1998 to September 1998. Also noteworthy is the winners portfolio on its own. The winners portfolio outperforms the market in 6 of the 9 bear markets and 6 of the 9 bull markets! While we might expect winners to outperform in the bull markets, outperformance in the bear markets is astonishing. The commonly-held perception of long-only momentum investing as speculative seems to be inaccurate, at least for the sample period examined. Further, when the winners portfolio underperforms in bear markets it is always by a very small margin, and usually with a standard deviation similar to the market. I will remind the reader that the winners portfolio achieves an abnormal (defined as return above the market) average return of 3.17% per month annualized for the time period examined. Moreover, the winners portfolio achieves a cumulative return over the entire 1964-2003 sample period of 29,176% vs. the cumulative market buy-and-hold return of 8,596%. While the winners portfolio definitely bears more risk in terms of industry concentration than the buy-and-hold market portfolio, this finding is surprising nonetheless.

Table 13

Returns to Zero-Cost Momentum Strategy Versus Buy and Hold in Bull and Bear Markets (1964 - 2003)
6-Month Lag, 6-Month Hold, 30 Industries, 6 Purchased/Sold

Bull and Bear markets are defined by Standard & Poor's, and approximately follow the following rule: a 20% decline in the S&P 500 Composite Price Index indicates a bear market (as measured from the previous peak to the trough of the S&P 500 Composite Price Index), and a 20% rise in the S&P 500 Composte Price Index indicates a bull market (as measured from the previous bottom to the peak of the S&P 500 Composite Price Index). Bull and bear market time periods were obtained from Global Financial Data. Average monthly returns and standard deviations for monthly periods are shown. Market is defined as the 'buy and hold', or passive strategy of buying all industries and rebalancing to equal weights every month. Beta is calculated according to the CAPM, i.e. a simple regression of the zero-cost portfolio's returns on the returns of the market.

All figures in % except dates.

Time Period	Market	Market Return	Market Std Dev	Winners Returns	Winners Std Dev	Winners - Market	Losers Return	Losers Std Dev	Market - Losers	Winners - Losers	Win - Los Std Dev	Win - Los Beta
10/2002 - 12/2003	Bull	2.55	3.98	2.25	3.79	-0.30	3.56	6.15	-1.01	-1.32	4.67	-0.56
04/2000 - 09/2002	Bear	-0.43	4.65	-0.46	5.31	-0.03	-1.14	6.58	0.71	0.68	6.34	-0.32
10/98 - 03/2000	Bull	1.44	4.26	3.31	5.19	1.87	0.29	4.89	1.15	3.02	5.57	-0.23
08/98 - 09/98	Bear	-4.93	14.35	-5.07	14.15	-0.14	-3.97	16.36	-0.96	-1.09	2.22	-0.15
11/90 - 07/98	Bull	1.51	3.22	1.60	3.34	0.09	1.33	3.46	0.18	0.27	2.16	-0.02
08/90 - 10/90	Bear	-6.75	4.08	-6.06	4.04	0.69	-7.34	3.85	0.59	1.28	0.27	0.04
12/87 - 07/90	Bull	1.74	3.87	1.65	3.86	-0.09	1.59	3.96	0.15	0.07	2.27	-0.01
09/87 - 11/87	Bear	-11.12	12.81	-10.39	14.95	0.73	-10.36	10.87	-0.76	-0.03	4.25	0.32
08/82 - 08/87	Bull	2.29	4.56	2.39	4.84	0.10	2.03	4.59	0.26	0.36	3.23	0.08
12/80 - 07/82	Bear	-0.41	3.70	-0.11	3.80	0.30	-1.00	4.30	0.59	0.89	3.23	-0.09
03/78 - 11/80	Bull	2.15	5.39	2.56	6.45	0.41	2.07	5.00	0.08	0.49	3.17	0.25
10/76 - 02/78	Bear	-0.15	3.27	0.22	3.36	0.37	-0.57	3.52	0.42	0.79	1.72	-0.04
10/74 - 09/76	Bull	2.98	6.31	2.66	6.28	-0.32	3.56	6.94	-0.58	-0.90	3.26	-0.12
01/73 - 09/74	Bear	-2.77	5.37	-1.63	4.81	1.14	-3.40	7.30	0.63	1.77	4.43	-0.49
06/70 - 12/72	Bull	1.70	4.19	1.84	3.86	0.14	1.62	5.16	0.08	0.23	3.18	-0.34
12/68 - 05/70	Bear	-2.03	5.27	-1.47	5.18	0.56	-2.46	5.22	0.43	0.99	1.80	-0.03
10/66 - 11/68	Bull	2.51	3.96	3.05	4.31	0.54	2.07	4.33	0.44	0.98	2.67	-0.03
02/66 - 09/66	Bear	-2.28	3.37	-2.42	4.90	-0.14	-2.34	2.36	0.06	-0.09	3.35	0.78

Table 14

Returns to Zero-Cost Momentum Strategy Versus CRSP Value-Weighted Index in Bull and Bear Markets (1964 - 2003)
6-Month Lag, 6-Month Hold, 30 Industries, 6 Purchased/Sold

Bull and Bear markets are defined by Standard & Poor's, and approximately follow the following rule: a 20% decline in the S&P 500 Composite Price Index indicates a bear market (as measured from the previous peak to the trough of the S&P 500 Composite Price Index), and a 20% rise in the S&P 500 Composposte Price Index indicates a bull market (as measured from the previous bottom to the peak of the S&P 500 Composite Price Index). Bull and bear market time periods were obtained from Global Financial Data. Average monthly returns and standard deviations for monthly periods are shown. Market is defined as the CRSP Value-Weighted index. Beta is calculated according to the CAPM, i.e. a simple regression of the zero-cost portfolio's returns on the returns of the market.

All figures in % except dates.

Time Period	Market	Market Return	Market Std Dev	Winners Returns	Winners Std Dev	Winners - Market	Losers Return	Losers Std Dev	Market - Losers	Winners - Losers	Win - Los Std Dev	Win - Los Beta
10/2002 - 12/2003	Bull	2.36	3.95	2.25	3.79	-0.11	3.56	6.15	-1.20	-1.32	4.67	-0.77
04/2000 - 09/2002	Bear	-1.92	5.53	-0.46	5.31	1.46	-1.14	6.58	-0.78	0.68	6.34	-0.39
10/98 - 03/2000	Bull	2.58	4.17	3.31	5.19	0.73	0.29	4.89	2.29	3.02	5.57	0.32
08/98 - 09/98	Bear	-4.83	15.65	-5.07	14.15	-0.24	-3.97	16.36	-0.86	-1.09	2.22	-0.14
11/90 - 07/98	Bull	1.42	3.14	1.60	3.34	0.18	1.33	3.46	0.09	0.27	2.16	0.08
08/90 - 10/90	Bear	-5.56	4.03	-6.06	4.04	-0.50	-7.34	3.85	1.78	1.28	0.27	0.05
12/87 - 07/90	Bull	1.29	3.54	1.65	3.86	0.36	1.59	3.96	-0.30	0.07	2.27	0.03
09/87 - 11/87	Bear	-10.89	10.60	-10.39	14.95	0.50	-10.36	10.87	-0.53	-0.03	4.25	0.37
08/82 - 08/87	Bull	1.85	4.25	2.39	4.84	0.54	2.03	4.59	-0.18	0.36	3.23	0.09
12/80 - 07/82	Bear	-1.30	3.63	-0.11	3.80	1.19	-1.00	4.30	-0.30	0.89	3.23	-0.14
03/78 - 11/80	Bull	1.82	4.97	2.56	6.45	0.74	2.07	5.00	-0.25	0.49	3.17	0.29
10/76 - 02/78	Bear	-0.07	3.10	0.22	3.36	0.29	-0.57	3.52	0.51	0.79	1.72	-0.03
10/74 - 09/76	Bull	2.30	5.73	2.66	6.28	0.36	3.56	6.94	-1.26	-0.90	3.26	-0.11
01/73 - 09/74	Bear	-3.08	4.61	-1.63	4.81	1.45	-3.40	7.30	0.32	1.77	4.43	-0.45
06/70 - 12/72	Bull	1.48	3.52	1.84	3.86	0.36	1.62	5.16	-0.14	0.23	3.18	-0.39
12/68 - 05/70	Bear	-2.09	4.80	-1.47	5.18	0.62	-2.46	5.22	0.37	0.99	1.80	-0.04
10/66 - 11/68	Bull	1.67	3.51	3.05	4.31	1.38	2.07	4.33	-0.40	0.98	2.67	-0.08
02/66 - 09/66	Bear	-2.31	3.21	-2.42	4.90	-0.11	-2.34	2.36	0.03	-0.09	3.35	0.66

4 CONCLUSION

Grinblatt and Moskowitz (1999) find that intermediate-term momentum is strongly related to industry groups. The results of this study indicate that profits to an intermediate-term industry momentum strategy vary significantly with the number of industries included in the universe and the number of industries purchased and sold. For example, the average difference (across 6-month lag strategies) in average monthly profits between the 30-industry strategy that purchases/sells the top/bottom 3 industries and the 30-industry strategy that purchases/sells the top/bottom 9 industries amounts to 3.75 percent per month annualized. Further, the average difference (across the 6-month lag strategies and across the number of industries purchased and sold) between the strategy that includes 30 industries in the universe and the strategy that includes 12 industries in the universe amounts to 2.92 percent per month annualized. These differences equate to significant incremental annual returns by most standards. This finding is inconsistent with the Grinblatt and Moskowitz conclusion that industries account for almost all of the momentum profits observed in individual stocks. Indeed, it is almost tautological that profits to momentum trading strategies would decrease as we decreased the number of industries in the universe. For example, imagine the profits to momentum strategies in a two-industry universe. The return-dilution effect within industries would eliminate any opportunity for momentum profits. While it is clear that Grinblatt and Moskowitz have found a significant relationship between momentum profits and industry groups, industry groups can not account for all of the profits to momentum trading strategies. This finding begs the question, "what level of industry breakdown best captures the economic differences between industries?"

The results also clearly indicate that so-called 'cyclical' industries are the most frequently purchased and sold industries in the momentum strategies. While we would expect these cyclical industries to exhibit the most sensitivity to the business cycle, this does not explain why these industries exhibit the most momentum. For an explanation of this phenomenon we could look to a combination of Berk, Green and Naik (1999) and Hong and Stein (1999). Berk, Green and Naik (1999) demonstrate that changes in a firm's growth options that are related to its systematic risk can generate momentum in its returns. Since growth opportunities are likely more correlated among firms within industries versus across industries, and likely depend on industry-specific attributes, it is conceivable that their model would generate industry momentum. Further, Hong and Stein (1999) suggest that slow information diffusion into prices causes an initial underreaction to news, but the presence of 'momentum traders' seeking to exploit the slow price movement causes subsequent reversals. If we imagine that cyclical firms experience a rush of new information at turning points in the business cycle, it is conceivable that the slow incorporation of this rush of new information would create increased momentum for these industries versus non-cyclical industries. In other words, information related to cyclical industries might come in infrequent large chunks, while information related to other industries may be distributed more smoothly over time. In addition, there is no significant relationship between the frequency that an industry is featured in the winner and loser portfolios and its average monthly return over the sample period. This is further evidence that the factors driving the 'amount' of momentum that particular industries exhibit are related to non-return-based characteristics.

Industry momentum varies significantly throughout the calendar year, and calendar month returns vary significantly depending on how many industries are included in the universe. June and December are by far the most significant months for industry momentum returns irrespective of the number of industries examined. June and December returns account for 46.9%, 70.5% and 61.9% of the total return available throughout the calendar year for the 30-industry, 17-industry and 12-industry strategies respectively.

The zero-cost momentum trading strategy outperforms in every bear market and underperforms in every bull market since February 1966 except the tech bubble of the late 1990s. During the tech bubble, the zero-cost momentum trading strategy outperformed the market by a factor of 2.1 times, as winners significantly outperformed and losers significantly underperformed. Further, the zero-cost momentum strategy is incredibly resilient in times of market crisis, such as the market crises of late 1998, late 1990 and late 1987. The zero-cost momentum strategy outperforms the market by an average monthly return of 7.65% over these three periods. In effect, the zero-cost momentum strategy acts as a 'quick-response mechanism' to market price signals in a market crisis. The results also indicate that the winners portfolio outperforms the market in 6 of the 9 bear markets and 6 of the 9 bull markets (8 of the 9 bull markets when compared to the Value-Weighted CRSP Index)! Further, the winners portfolio does not significantly underperform the market in any bull or bear market. The commonly held perception of long-only momentum investing as speculative seems to be inaccurate, at least for the sample period examined. With reasonable risk, the winners portfolio achieves a cumulative return over the entire 1964-2003 sample period of 29,176% versus the cumulative market buy-and-hold return of 8,596% and the cumulative Value-Weighted CRSP return of 1,423%

(all returns exclude dividends). This is an extraordinary return for a strategy that outperforms in 6 out of 9 bear markets, even when considering the strategy's industry concentration risk.

The findings of this study carry important implications for investment managers of all types. An investment manager that wants to implement an industry momentum strategy has to consider how many industries to examine in the universe and how many industries to purchase and sell. More importantly, the manager may be limited in the amount of choice he has with respect to these variables. For example, the manager may have to implement an industry momentum strategy using investment products such as exchange-traded funds and/or open-end mutual funds. Alternatively, the manager may choose to implement a strategy that evaluates a given set of industries and purchases and sells only the five largest companies in any one industry. Either way, the costs and difficulties associated with implementing an industry momentum strategy may be prohibitive. A 6-month lag, 6-month hold strategy would replace $1/6^{th}$ of the portfolio every month. On top of transaction costs, a strategy that uses exchange-traded products might experience a dilution of profits due to the discount or premium to net asset value on the exchange-traded products. On the other hand, a strategy that uses open-end mutual funds will have to contend with management expense ratios and potential limits on the amounts of fund shares that can be purchased. Also, a mix of different exchange-traded or mutual fund products is not likely to cover the entire universe of stocks, so that there may always be some stocks that a manager can't get exposure to, and these stocks may play an important role in a particular industry's momentum. That said, the 3.17 percent per month annualized outperformance of the 6-month lag, 6-month hold, 30-industry strategy that purchases and sells 6 industries versus the buy-and-hold strategy understates its value in the marketplace. This strategy actually outperforms the Value-Weighted CRSP Index by 7.96 percent per month annualized over the same period. Even if this outperformance was cut in half by transaction costs, there would still be a significant opportunity for increased returns for those managers willing to take on industry concentration risk.

REFERENCE LIST

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options, and security returns, *Journal of Finance* 54, 1553-1607.

Cao, Melanie, and Jason Z. Wei, 2002, Uncovering sector momentums, *Canadian Investment Review* 15, 14-22.

Chan, Kalok, Allaudeen Hameed, and Wilson Tong, 2000, Profitability of momentum strategies in the international equity markets, *Journal of Financial and Quantitative Analysis* 35, 153-172.

Chan, Louis K. C., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *Journal of Finance* 51, 1681-1713.

Conrad, Jennifer, and Gautum Kaul, 1998, An anatomy of trading strategies, *Review of Financial Studies* 11, 489-520.

DeBondt, Werner F. M., and Richard Thaler, 1985, Does the stock market overreact?, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 53, 427-465.

Fama, Eugene F., and Kenneth R. French, 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55-84.

French, Kenneth R., Accessed: November 29, 2004, Data Library, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Grinblatt, Mark, and Tobias J. Moskowitz, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249-1290.

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995, Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, *The American Economic Review* 85, 1088-1105.

Grundy, Bruce D., and J. Spencer Martin, 2001, Understanding the nature of the risks and the source of the rewards to momentum investing, *The Review of Financial Studies* 14, 29-78.

Hill, Arthur, Accessed: November 29, 2004, Indicator Analysis - MACD, http://stockcharts.com/education/IndicatorAnalysis/indic_MACD1.html.

Hong, Harrison, and Jeremy C. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 54, 2143-2184.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies, *Journal of Finance* 55, 265-295.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699-720.

Jegadeesh, Narasimhan, and Sheridan Titman, 2002, Cross-sectional and time series determinants of momentum returns, *Review of Financial Studies* 15, 143-157.

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *Review of Financial Studies* 3, 175-205.

Rouwenhorst, K. Geert, 1998, International momentum strategies, *Journal of Finance* 53, 267-284.

Stockcharts.com Inc., Accessed: November 29, 2004, Market Analysis - Dow Theory, *http://stockcharts.com/education/MarketAnalysis/dowtheory1.html*.