Do Industries Explain Momentum?*

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Current Draft: October 1998

*We thank Ty Callahan, Kent Daniel, Gordon Delianedis, Gene Fama, Rick Green, Jonathan Howe, Olivier Ledoit, Richard Roll, Pedro Santa-Clara, Sheridan Titman, Ralph Walkling, Russell Wermers, David Wessels, and seminar participants at UCLA, Yale, Harvard, Rochester, Ohio State, Wharton, Columbia, Duke, University of Colorado at Boulder, University of Texas at Austin, University of Chicago, Northwestern, Michigan, and the 1998 WFA meetings in Monterey, CA for valuable comments and insights.

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This paper documents a strong and prevalent momentum effect in industry components of stock returns that accounts for much of the individual stock momentum anomaly. Specifically, momentum investment strategies, which buy past winning stocks and sell past losing stocks, are significantly less profitable once we control for industry momentum. By contrast, industry momentum investment strategies, which buy stocks from past winning industries and sell stocks from past losing industries, appear highly profitable, even after controlling for size, book-to-market equity, individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences.

1 Introduction

Both investment theory and its application to the management of portfolios critically depend on our field's understanding of stock return persistence anomalies. Determining whether these anomalies are rooted in behaviors that can be exploited by more rational investors at low risk has profound implications for our view of market efficiency and optimal investment policy. The ability to outperform buy and hold strategies by acquiring past winning stocks and selling past losing stocks, commonly referred to as "individual stock momentum," remains one of the most puzzling of these anomalies, both because of its magnitude (up to 12% per year abnormal return per dollar long on a self-financing strategy) and because of the peculiar horizon pattern that it seems to follow. Trading based on individual stock momentum appears to be a poor strategy when using a short historical horizon for portfolio formation (especially under 1 month); it is a highly profitable strategy at intermediate horizons (up to 24 months, although it is strongest in the 6 to 12 month range); and is once again a poor strategy at long horizons.[1]

This paper largely focuses on the positive persistence in stock return performance (or momentum effect) over intermediate investment horizons (6 to 12 months) and explores various explanations for its existence. We identify industry momentum as the source of much of the momentum trading profits at these horizons, shedding light on various risk and behavioral hypotheses that have been offered for this anomaly. Among these explanations is (i) Jegadeesh and Titman's (1993) behavioral explanation, that individual stock momentum is driven by "delayed price reactions to firm-specific information" (p. 67) and (ii) Conrad and Kaul's (1998) claim that momentum profits are "entirely due to the contribution of cross-sectional variance in mean returns to total profits" (p. 3).

Both of these explanations seem implausible. Jegadeesh and Titman's behavioral hypothesis should at least be constrained by the fact that some rational investors exist and that behaviorally-based momentum cannot exist in equilibrium if these rational investors perceive momentum as an arbitrage opportunity. However, if the bulk of investors persistently and *irrationally* underreact to information that is truly firm specific (and thus uncorrelated across firms), then rational investors can profit from their irrational counterparts with siz-

[1] Anomalous strong autocorrelation in stock returns at various horizons have been documented by (among others) DeBondt and Thaler (1985), Lo and MacKinlay (1988), Jegadeesh (1990), and Jegadeesh and Titman (1993).

able positions. In an economy which has a large number of stock returns generated by a factor model, there are virtually no limits to this arbitrage. A self-financing momentum portfolio that is long high past return stocks and short low past return stocks (weighted to have a similar factor beta configuration as the winner portfolio) could be created with zero factor risk. Such a portfolio would have firm-specific risk that was almost perfectly diversified away and, because of momentum, would enjoy a positive expected return. It seems unlikely that no rational investors exist who would exploit such a low-risk near arbitrage. If behavioral patterns about firm-specific information 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. One contribution of this paper, therefore, is to show that since 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 it is far from an arbitrage.

Conrad and Kaul's arguments also strike us as implausible simply because of the size of momentum trading profits and the signal to noise ratio in the sorting procedures used to generate momentum strategy buys and sells. Our priors about the cross-sectional distribution of ex-ante mean returns in relation to volatility suggests that winner-loser sorts over horizons from 6 months to a year are likely to generate only negligible differences between the ex-ante means of the winner and loser portfolios. Winners and losers are largely going to be determined by luck, rather than ex-ante mean differences. Moreover, such sorts become more accurate the longer the horizon, yet the profitability from momentum strategies based on performance over the past 6 months seems as large, if not larger than the profits from a momentum strategy using past performance of 12 months or more, and momentum profits based on performance over the past 24 or 36 months are negligible, even becoming negative when based on sorts longer than 36 months.

Isolating the components of momentum profits, we find that neither persistence in firm-specific return components nor dispersion in unconditional mean returns explains the profitability of momentum strategies. Rather, we find strong evidence that persistence in industry return components generate significant profits and may account for much of the profitability of individual stock momentum strategies. Specifically, we show that:

- Industries themselves 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 robust to various specifications and methodologies, and appear to be profitable even among the largest, most liquid stocks, making them less subject to transaction costs than individual stock momentum strategies.

- Industry momentum strategies are more profitable than individual stock momentum strategies.

- The profitability of the industry strategies typically are equally driven by the long and short positions. Again, this makes them more appealing than individual stock momentum strategies, which are largely driven by selling past losers, and thus may be hindered by short sales constraints.

- Unlike individual stock momentum, industry momentum is strongest in the short-term (at the 1 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 1-month) performance of the industry and individual stock momentum strategies are completely opposite, yet the signs of their intermediate and long-term performance are identical.

The rest of the paper is organized as follows. Section 2 briefly describes the data and formation of industries. Section 3 presents a motivation for the paper, based on a simple return generating process, and discusses various sources of momentum profits. Section 4 isolates the sources of momentum profits and finds a large and significant industry influence. Section 5 then analyzes the robustness of our results, finding strong industry momentum independent from individual stock momentum, the cross-sectional variation in mean returns, and microstructure effects. Section 6 then evaluates our results using Fama-MacBeth regressions, which allows us to determine how industry momentum and individual stock momentum interact in explaining the cross-section of expected returns. Finally, Section 7 concludes the paper.

2 Data Description and Industry returns

Using the CRSP and COMPUSTAT data files, 20 value-weighted industry portfolios are formed every month from July, 1963 to July, 1995. Two digit Standard industrial Classification (SIC) codes[2] are used to form industry portfolios in order to maximize coverage of NYSE, AMEX, and NASDAQ stocks, while maintaining a manageable number of industries, and ensuring that each industry contains a large number of stocks for diversification. The two digit SIC groupings are similar to those employed by Boudoukh, Richardson, and Whitelaw (1994) and Jorion (1991). Table 1 provides a description of the industry portfolios and summary statistics on them. The average number of stocks per industry is 230, and the fewest number of stocks in any industry (except for Railroads) at any time is over 25. Therefore, virtually all portfolios are well-diversified in that they have negligible firm-specific risk.

Table 1 reports the average monthly raw excess returns of the 20 industries. An F-test of whether these mean returns differ across industries is rejected, suggesting there is little cross-sectional variation in our industry sample means. In addition, we adjust industry returns for size and book-to-market equity (BE/ME), since much research has documented the ability of these variables to capture the cross-section of expected returns.[3] Table 1 reports the size and BE/ME adjusted industry returns, where stocks within the industry are matched with well-diversified portfolios of similar size and BE/ME, and the value-weighted average of stock returns in excess of these size and BE/ME benchmarks represents the industry abnormal return.[4] As Table 1 shows, there is little evidence that unconditional abnormal industry returns exist per se,[5] and we fail to reject an F-test that the abnormal returns are

[2]The SIC codes are obtained from CRSP, which reports the time-series of industry classification codes. COMPUSTAT only reports the most recent SIC codes. Employing the COMPUSTAT codes does not alter our conclusions, however.

[3]See, for example, Banz (1981), Rosenberg, Reid, and Lanstein, (1985), Fama and French (1992), and Daniel and Titman (1997).

[4]Our control adjusts returns for the effects of size and BE/ME, by first sorting stocks into size quintiles, and then within each size quintile, sorting stocks into BE/ME quintiles, where stocks are value-weighted within these groups. Stock j is then matched with one of the 25 portfolios based on its size and BE/ME characteristic at time $t-1$, and the return of the matched portfolio is subtracted from stock j's return at time t. We employ this characteristically-matched portfolio adjustment method as opposed to a regression on pre-specified factor portfolios (i.e., Fama and French (1993)), in order to avoid estimation issues regarding factor loadings and because Daniel and Titman (1997) find that characteristics better capture cross-sectional variation in mean returns than do factor loadings.

[5]Indeed, each of the 20 univariate tests that industry abnormal returns significantly differ from zero fail to reject the 5% significance derived from the Bonferroni inequality, which accounts for the inspection of multiple industries.

different across industries.

3 Motivation

In this section, we present a simple model of returns that allows us to illustrate the potential sources of momentum profits and provides the intuition for subsequent tests designed to isolate each of the these potential sources.

3.1 Return Generating Process

Consider the following multifactor linear process for stock returns (which assumes a constant risk-free return for expositional simplicity),

$$\tilde{r}_{jt} = r_f + \sum_{k=1}^{K} \beta_{jk} \tilde{R}_{kt} + \sum_{m=1}^{M} \theta_{jm} \tilde{z}_{mt} + \tilde{\epsilon}_{jt} \tag{1}$$

where $\tilde{r}_{jt}$ is the return of stock j at time t, $\tilde{R}_{kt}$ are the returns of zero cost portfolios that mimic the most important economy-wide factors (which are the source of unconditional return premia for securities returns sensitive to them), β_{jk} are the factor portfolio sensitivities, $\tilde{z}_{mt}$ are correlated components of returns across assets orthogonal to the K factors, (normalized to have zero unconditional mean, but, being less pervasive than the factors mimicked by the R's, do not bear unconditional risk premia), θ_{jm} are stock j's sensitivities to the z components, and $\tilde{\epsilon}_{jt}$ are firm-specific return components (with mean zero) which are uncorrelated across assets.

It is useful to think of the R's as being well-proxied for by the Fama and French (1993) book-to-market, size, and market "factor" portfolios, normalized for expositional purposes (without loss of generality) to be orthogonal to one another.[6] Empirical research in finance has suggested that these factor portfolios capture the cross-section of expected returns within the feasible set of *semi-passive* strategies (in a sense to be defined shortly). That is, the unconditional expected return of stock j is,

$$\mu_j = r_f + \sum_{k=1}^{K} \beta_{jk} E[\tilde{R}_{kt}]. \tag{2}$$

[6] Alternatively, we can think of $\sum_{k=1}^{K} \beta_{jk} \tilde{R}_{kt}$ as being the size and BE/ME matched portfolios of Daniel and Titman (1997), described earlier.

Equivalently, we are stating that mean variance efficient semi-passive portfolios have θ's of zero and have well diversified holdings of large numbers of assets, so that the portfolio ϵ negligibly differs from zero. These are *semi-passive* strategies in that they may need to adjust the portfolio weights on assets that change their sensitivities to the size, book-to-market, and market factors, and as the unconditional return premia associated with these factors change. However, in comparison with a momentum strategy, the turnover inherent in an optimal semi-passive strategy is rather low. For expositional simplicity, therefore, we will pretend that the changes in sensitivity to these semi-passive portfolios (i.e., book-to-market, size, etc.) that would generate this turnover do not exist; hence, the lack of time subscripts on the factor sensitivities and the μ's.

The z's can be thought of as the orthogonal projection of industry portfolio returns (i.e., industry factors) onto the optimal semi-passive portfolios (such as the Fama-French factor portfolios). While, in principle, there could be other sources of correlation between security returns besides industry that are less pervasive than the R's, and thus would qualify as z's, expositional simplicity dictates that we interpret the z's as only being industry-related. As documented in Table 1 and noted above, industries, although a source of correlation between groups of stocks, do not appear to have unconditional risk premia per se. Thus, as implicitly suggested above, the β's may be associated with the unconditional mean return μ, but the θ's should not be related to μ. However, there is no theoretical reason for this to be true. For example, the oil industry return, even after controlling for size, book-to-market, and market effects, is probably not very diversifiable. It could carry a positive, zero, or negative risk premium depending on whether the economy in the aggregate has to bear oil industry risk through its supply of oil or its future consumption of oil.[7] However, empirical research, including that in this paper, documents that the hypothesis of zero unconditional industry risk premia per se cannot be rejected. By contrast, the firm-specific return components should carry no risk premium in the absence of arbitrage, and thus do not affect μ.

Even if K factor-mimicking portfolios plus a risk-free asset span the unconditional mean-variance efficient frontier, the conditional mean-variance efficient frontier may not exhibit $K+1$ fund separation. If active portfolio strategies, such as momentum, which require high turnover, generate larger Sharpe ratios than the semi-passive strategies that are generated by analyzing the sensitivities of stocks to size, book-to-market, and market factors alone,

[7] For a discussion of this, see Hirshleifer (1988).

then additional risky portfolios besides the R's are required to explain the cross-section of *conditional* expected returns. Assuming that the conditional means of the R's, z's, and ϵ's can change, then the expected returns of assets conditional on the information at time t, ϕ_t, are represented by the equation

$$E[\tilde{r}_{jt}|\phi_t] = r_f + \sum_{k=1}^{K} \beta_{jk} \left(E[\tilde{R}_{kt}|\phi_t] \right) + \sum_{m=1}^{M} \theta_{jm} E[\tilde{z}_{mt}|\phi_t] + E[\tilde{\epsilon}_{jt}|\phi_t] \tag{3}$$

By construction, the K factor portfolios, industry components, and idiosyncratic terms are contemporaneously uncorrelated with each other, both conditionally and unconditionally. We also assume

$$E[\tilde{R}_{kt}\tilde{R}_{lt-1}] = 0, \ \forall k \neq l; \quad E[\tilde{R}_{kt}\tilde{\delta}_{mt-1}] = 0, \ \forall k, m; \quad E[\tilde{R}_{kt}\tilde{\epsilon}_{jt-1}] = 0, \ \forall k, j;$$
$$E[\tilde{\delta}_{mt}\tilde{\delta}_{nt-1}] = 0, \ \forall m \neq n; \quad E[\tilde{\delta}_{mt}\tilde{\epsilon}_{jt-1}] = 0, \ \forall m, j; \quad E[\tilde{\epsilon}_{jt}\tilde{\epsilon}_{it-1}] = 0, \ \forall j \neq i.$$

where $E[\tilde{\delta}_{mt}] = 0, \forall m$ and $E[\tilde{\epsilon}_{jt}] = 0, \forall j$. This assumed structure for stock returns, where own autocorrelations are possible, but cross-autocorrelations are not, generates a particularly simple decomposition of momentum profits.

3.2 Analytical Decomposition of Momentum Profits

Positive momentum in returns implies that stocks which outperformed the average stock in the last period (however defined), will outperform the average stock in the next period. Thus, to understand momentum, we need to focus on conditional expected returns, where the conditioning information, ϕ_t, consists of last period's values for the return components, specifically, $\tilde{R}_{kt-1}$, $\tilde{\delta}_{mt-1}$, and $\tilde{\epsilon}_{it-1}$.

There are various ways to form portfolios that help us analyze momentum. For example, past research has largely focused on long-short investments in various decile combinations, with equal weights on the stocks in the longs and shorts. This equal-weighting of the longs and shorts is used because the economic magnitude of the returns to such a self-financing strategy are easy to interpret. It is also possible to focus on self-financing portfolios with weights that are linear functions of measured momentum. One such portfolio, which has returns that are highly correlated with the decile portfolios used in past research has returns that are expressed as

$$E[(\tilde{r}_{jt} - \overline{r}_t)(\tilde{r}_{jt-1} - \overline{r}_{t-1})] > 0. \tag{4}$$

where $\overline{r}_t$ is the cross-sectional or equal-weighted average return of stocks at time t (a bar over a variable represents its cross-sectional average in this section). Equation (4) represents a self-financing momentum investment strategy where $(\tilde{r}_{jt-1} - \overline{r}_{t-1})$ is the amount invested in stock j at time t, funded by shorting the same amount in the equal-weighted portfolio. There are notational advantages to decomposing the returns to the linear portfolio expressed above, as opposed to analytically decomposing the returns of the equal-weighted decile-based portfolios.

In this paper, we take liberties in interpreting the returns of the self-financing momentum portfolios studied in this paper, which are based on a hybrid of the decile form of portfolio weighting, to draw inferences about the parameters of the decomposition of returns from a linear portfolio weighting, as expressed in equation (4). However, we believe that these liberties do not affect the inferences we draw about either functional form of the portfolio weighting.[8]

Based on the assumed process for generating stock returns, momentum profits can be decomposed as follows,

$$\begin{aligned} E[(\tilde{r}_{jt} - \overline{r}_t)(\tilde{r}_{jt-1} - \overline{r}_{t-1})] &= (\mu_j - \overline{\mu})^2 + \sum_{k=1}^{K} (\beta_{jk} - \overline{\beta}_k)^2 \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) \\ &\quad + \sum_{m=1}^{M} (\theta_{jm} - \overline{\theta}_m)^2 \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1}) + \mathrm{Cov}(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1}). \end{aligned} \tag{5}$$

Averaging over all N stocks, momentum trading profits equal,

$$= \sigma_\mu^2 + \sum_{k=1}^{K} \sigma_{\beta_k}^2 \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) + \sum_{m=1}^{M} \sigma_{\theta_m}^2 \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1}) + \frac{1}{N} \sum_{j=1}^{N} \mathrm{Cov}(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1}), \tag{6}$$

where σ_μ^2, $\sigma_{\beta_k}^2$, and $\sigma_{\theta_m}^2$ represent the cross-sectional variances of mean returns, portfolio loadings, and industry sensitivities, respectively.

This decomposition allows us to compare the relative magnitudes of these potential sources of profits. Equation (6) suggests that there are four sources of momentum trading profits from individual stocks. The first is σ_μ^2. This is the Conrad and Kaul (1998) hypothesis that momentum profits are solely driven by dispersion in unconditional expected returns. The second term, $\sum_{k=1}^{K} \sigma_{\beta_k}^2 \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1})$ is the contribution to momentum of serial correlation in the unconditionally efficient (semi-passive) portfolios. Thus, if profits

[8] For instance, we document a 0.95 correlation between the profits generated from our decile-based strategy and the one specified in equation (4), and a 0.93 correlation between our decile-based strategy and the decile-based strategy in Jegadeesh and Titman (1993).

from a book-to-market, size, or market beta-based strategy exhibit persistence, this second term would be positive. The third term, $\sum_{m=1}^{M} \sigma^2_{\theta_m} \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1})$, is the contribution to momentum of serial correlation in industry returns. Finally, we have serial covariation in firm-specific components ($\mathrm{Cov}(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1})$) as a contributor to momentum. The Jegadeesh and Titman (1993) hypothesis is that this latter component is primarily responsible for momentum trading profits.

Evidence in the next section demonstrates that, at least for 6-month momentum, most of the trading profits arise from the third term, $\sum_{m=1}^{M} \sigma^2_{\theta_m} \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1})$. Thus, although the unconditional expected return on industry components is zero ($E[\tilde{\delta}_{mt}] = 0$), conditioning on information in past returns, the conditional expectation of industry return components is non-zero ($E[\tilde{\delta}_{mt}|\tilde{r}_{jt-1}] = E[\tilde{\delta}_{mt}|\tilde{\delta}_{mt-1}] \neq 0$). Thus, industry components may influence the conditional expectation of stock returns, and some combination of factors and industry effects may be conditionally mean-variance efficient, implying that the cross section of expected returns conditional on last period's returns can be reasonably summarized by the equation

$$E[\tilde{r}_{jt}|\tilde{r}_{jt-1}] = r_f + \sum_{k=1}^{K} \beta_{jk} E[\tilde{R}_{kt}] + \sum_{m=1}^{M} \theta_{jm} E[\tilde{\delta}_{mt}|\tilde{\delta}_{mt-1}]. \tag{7}$$

In the next section, we estimate the relative magnitudes of the components in equation (6) for the 6-month horizon. A later section of the paper addresses the generalizability of this result to other momentum horizons.

4 Isolating Sources of Momentum Trading Profits

4.1 Momentum Investment Strategies

We form winners minus losers self-financing momentum investment strategies in individual stocks by ranking stocks based on their prior L-month returns and forming a zero-cost portfolio of the highest past L-month return stocks funded by shorting a portfolio of low past return stocks, holding these positions over the next H months. This is the procedure used in Jegadeesh and Titman (1993), who focus much of their analysis on the $L = 6$ month lagged, $H = 6$ month holding period strategy. For brevity and ease of comparison, we will do the same. For example, the 6-month, 6-month strategy at time t entails ranking stocks

based on their $t-6$ to $t-1$ returns, and computing the value-weighted return of the highest 30% of stocks *every month* from t to $t+5$ minus the value-weighted return of the lowest 30% of stocks every month from t to $t+5$. This procedure is then repeated at time $t+1$, and so on. That is, we maintain our selection of winning and losing stocks over the next 6 months. This lengthy holding period is consistent with Jegadeesh and Titman (1993). If investors are underreacting to past news, the underreaction is to the new information that is likely to come out over a 6-month future period, rather than information that is immediate.

We employ the same technique as Jegadeesh and Titman (1993) to avoid test statistics that are based on overlapping returns. This technique makes use of the fact that ranking on the past six months and holding for the next six months produces a time series of monthly returns where each month's return is a combination of six ranking strategies. For example, a January 1992 momentum strategy return is 1/6 determined by winners-losers from July 1991 through December 1991, 1/6 by rankings from May 1991 through November 1991, 1/6 by rankings from April 1991 through October 1991, and so on. Note that the December return is only a small component of one of the six ranking strategies. We later employ the same technique to generate the monthly profits of an industry momentum strategy. Hence, it would be wrong to attribute more than a negligible portion of the January return that we are analyzing to bid-ask bounce (in the case of individual stock momentum) or a lead-lag effect (in the case of industry momentum).[9]

4.1.1 Raw Profits

We employ 30% breakpoints to determine winners and losers, and value-weight the returns of stocks with momentum rankings in the top 30% and bottom 30% to compute the returns of the winning and losing portfolios. The individual stock momentum strategy (shown in Table 2 Panel A) generates a return (per dollar long) of about 6% per year, which is lower but statistically more significant than the momentum-based portfolio return reported in Jegadeesh and Titman (1993).[10]

[9] Lo and MacKinlay (1990) documented that positive serial correlation observed in portfolio returns is partly due to small firm returns being correlated with large firm returns in prior periods. This "lead-lag" effect is more acute in short-term contiguous returns.

[10] Jegadeesh and Titman (1993) document an annual 12% return per dollar long for their 6-month, 6-month strategy. Their return is larger than ours because they equal-weight the stocks within their winner and loser portfolios and they use 10% breakpoints. Equal-weighting stocks and employing 10% breakpoints increase the average return and volatility of the strategy, but do not change our conclusions. Equal-weighting stocks within the 30% categories (rebalancing monthly) produces profits of about 9.3% per year. We value-

4.1.2 Serial Covariation in the Factor Portfolios

The monthly rebalanced equally-weighted portfolio of all CRSP-listed stocks is useful for analyzing the source of this 6% per year return. The equal-weighted portfolio has two important properties: (i) it has negligible firm-specific risk (i.e., ϵ is close to zero and exhibits negligible variation over time) and (ii) its return is negligibly sensitive to the returns of any single industry, (i.e., $\overline{\theta}_m$ is very small for all m). Thus, the serial covariance of the equal-weighted portfolio of all stocks can be expressed as,

$$\mathrm{Cov}(\overline{r}_t, \overline{r}_{t-1}) = \sum_{k=1}^{K} \overline{\beta}_k^2 \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) \tag{8}$$

where t is a 6-month period. This allows us to isolate one of the components of momentum profits. Using *raw monthly-rebalanced* equal-weighted portfolio returns, we find, in accordance with Jegadeesh and Titman (1993), that the covariance of consecutive non-overlapping six-month returns on the equal-weighted index are insignificantly different from zero, $\mathrm{Cov}(\overline{r}_t, \overline{r}_{t-1}) = -0.0001$. Furthermore, since the risk premium of this portfolio is historically high (which implies that some of the β's of this portfolio must be large), serial covariation in the unconditionally efficient portfolios is not contributing to momentum profits. In addition, the serial covariance for consecutive 6-month returns of each of the three Fama and French (1993) factor-mimicking portfolios is $\mathrm{Cov}([Mkt - r_f]_t, [Mkt - r_f]_{t-1}) = -0.00008$, $\mathrm{Cov}(SMB_t, SMB_{t-1}) = 0.00007$, and $\mathrm{Cov}(HML_t, HML_{t-1}) = 0.00004$, none of which significantly differ from zero (likewise, the 6-month serial correlations for these three portfolios are -0.038, 0.102, and 0.061, respectively). Finally, employing momentum strategies on the Fama and French (1993) factor portfolios, by investing in the factor-mimicking portfolio which had the highest prior return and shorting the factor portfolio which had the lowest, produces negative profits of -0.0005 (t-stat = -0.42). This is overwhelming evidence that persistence in the returns of these portfolios does not exist. Thus, the R_k's cannot be driving momentum trading profits.

weight within the loser and winner portfolios because the DGTW return adjustment (used later) is based on matching stocks with value-weighted benchmarks. In addition, value weighting weakens the influence of the size effect and diminishes microstructure influences on profits. Again, however, equal weights were analyzed for robustness and, generating no significant differences, are not reported for brevity.

4.2 Industry Momentum Profits

Sorting industry portfolios (which value-weight stocks within the industry) based on their past 6-month returns, and investing equally in the top three industries, while shorting equally the bottom three industries (holding this position for 6 months) produces average monthly profits (shown in Table 2 Panel B) of 0.43%, identical in magnitude to those obtained from the momentum strategy for individual equities. We will show that the similarity of these magnitudes is not coincidental: Industry momentum profits are responsible for a large portion of the profits from an individual stock momentum strategy.

The existence of industry momentum profits of this magnitude is evidence against Jegadeesh and Titman's (1993) claim that firm-specific components drive momentum. Aggregating stocks into industry portfolios largely eliminates the firm-specific components of returns ($\tilde{\epsilon}$), since industries contain over 230 stocks on average. Also, as suggested earlier, if firm-specific components had been responsible for the profits of an individual stock momentum strategy, it would be possible to implement a nearly riskless arbitrage, which seems implausible.

The existence of industry momentum profits of the same magnitude as individual stock momentum profits is also evidence against Conrad and Kaul's (1998) claim that dispersion in mean returns drives momentum profits. The cross-sectional variance of ex-post mean industry monthly returns, $\sigma^2_{\mu_I}$, 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 (see Table 1) 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.[11]

We can summarize this conclusion more formally. Referring back to our model of returns in equation (1), industry momentum trading profits can be expressed as,

$$\frac{1}{20}\sum_{I=1}^{20} E[(\tilde{R}_{It} - \overline{r}_t)(\tilde{R}_{It-1} - \overline{r}_{t-1})] \quad = \quad \sigma^2_{\mu_I} + \sum_{k=1}^{K} \sigma^2_{\beta_{Ik}} \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) \tag{9}$$

[11] Conrad and Kaul's (1998) hypothesis implies that industry momentum profits should be significantly smaller than those for individual equities, because the cross-sectional variation in mean industry returns is much smaller than that for individual stock returns. When we employ equal-weighted industry portfolios in the industry momentum strategies, we obtain an average profit of .0081 per month or 10.2% per year (t-stat=7.71), which is about 90 basis points *higher* than the equal-weighted momentum strategy for individual equities, described in footnote 10.

$$+\sum_{m=1}^{M}\sigma^2_{\theta_{Im}}\mathrm{Cov}(\tilde{\delta}_{mt},\tilde{\delta}_{mt-1}),$$

where $\tilde{R}_{It}$ is the value-weighted return of stocks in industry I at time t.[12] Moreover, as previously noted, $\sigma^2_{\mu_I}$ is small and (at least for the Fama-French factor portfolios) $\mathrm{Cov}(\tilde{R}_{kt},\tilde{R}_{kt-1})<0$. Thus, the existence of industry momentum profits and the absence of factor serial correlation implies,

$$\sum_{m=1}^{M}\sigma^2_{\theta_{Im}}\mathrm{Cov}(\tilde{\delta}_{mt},\tilde{\delta}_{mt-1})>0. \tag{10}$$

4.2.1 Size and BE/ME Adjusted Profits

Previously, we provided industry momentum evidence that is inconsistent with the Conrad and Kaul (1998) conjecture that cross-sectional variation in mean returns accounts for much of the observed profits from an individual stock momentum strategy. In this subsection we show that sorting on six-month returns contributes negligibly to the cross-sectional variation in ex-ante mean returns. Moreover, to the extent that there is any variation due to sorting at all, it is due to the well-documented size effect and not to any statistical relation per se between historical six-month returns and ex-ante means.

If Conrad and Kaul's (1998) hypothesis is correct, momentum profits should be negligible after controlling for σ^2_μ. Our control is the Daniel and Titman (1997) size and BE/ME characteristic-adjusted return, described in Section 2, which we denote as

$$\tilde{r}^{sb}_{jt}\equiv\tilde{r}_{jt}-\tilde{R}^{SB_{j,t-1}}_t \tag{11}$$

where $\tilde{r}_{jt}$ is the return on security j, and $\tilde{R}^{SB_{j,t-1}}_t$ is the return on the size and BE/ME matched portfolio.[13] Adjusting holding period returns for size and BE/ME in this manner accounts for a large fraction of the cross-sectional variation in mean returns (as documented by Fama and French (1992, 1993, 1996), Daniel and Titman (1997), and Table 1), yet, as Table 2 shows, the 6-month, 6-month momentum strategy holding period returns adjusted for size and BE/ME remain strong, producing abnormal mean profits of 0.29% per month (with a highly significant t-stat of 3.34), which is about two thirds the size of the raw profits

[12] Note that there is no ϵ covariation term in the above formula since well-diversified portfolios have virtually no ϵ risk.

[13] Prior raw returns are always used to form portfolios, so that the selection of stocks into the 'winners' and 'losers' categories is the same.

and does not significantly differ from the raw return momentum number (the difference is about 13 basis points per month with a t-stat of 1.40). Since size and BE/ME account for a substantial portion of the cross-sectional variation in returns, yet explain a small fraction of momentum profits, cross-sectional dispersion in mean returns is not the likely source of these profits.

What is more telling however, is the serial pattern of the raw returns and the characteristic-adjusted returns. Prior to 1980, when the size effect was strong, there was a marginally significant (t-stat = 2.13) 22 basis point difference between the raw return from the momentum strategy and the characteristic-adjusted return. Since 1980 however, the size effect has disappeared, and the size and book-to-market adjusted momentum number is virtually the same as the raw return momentum number, differing by only 6 basis points (t-stat = 0.67).

Thus, a small portion of momentum profits have been due to cross-sectional differences in historical means because high momentum stocks are generally of smaller size than low momentum stocks. While this represents a cross-sectional historical return difference, it is not attributable to the statistical link between ex-ante and ex-post means per se. Moreover, to the extent that the size effect may have disappeared, we have no reason to believe that cross-sectional differences in means due to the momentum sort will account for any of the profits from a momentum strategy in the future.

Of course, it is always possible to assert that dispersion in mean returns remains after controlling for size and book-to-market and that it is this dispersion that drives the profitability of momentum strategies. However, this assertion does not seem credible, given the size of momentum profits, and plausible priors for the dispersion in ex-ante means (or ex-ante size and BE/ME adjusted means) of stock portfolios formed on sorts that employ only 6 months of historical returns.

4.2.2 DGTW Adjusted Profits

We have shown that size and BE/ME does not account for momentum profits. Consequently, Daniel, Grinblatt, Titman, and Wermers (1997), henceforth DGTW, in addition to adjusting

returns for size and BE/ME, also match stocks with similar momentum.[14] The first row of Table 2 Panel A reports the DGTW-adjusted momentum profits, as a baseline for the success of the DGTW return adjustment procedure. As the table demonstrates, DGTW momentum profits for individual securities do not significantly differ from zero, implying,

$$E[(\tilde{r}^*_{jt})(\tilde{r}_{jt-1} - \overline{r}_{t-1})] = 0, \tag{12}$$

where $\tilde{r}^*_{jt}$ is the DGTW-adjusted return and $\overline{r}^*_t \approx 0$ ($\overline{r}^*_t = 0.0003$ with a t-stat of 0.31). Since the equal-weighted portfolio exhibits no DGTW-adjusted return and is highly sensitive to market movements, we conclude that the DGTW adjustment, in addition to eliminating the premia associated with size and BE/ME, as well as the return impact of individual stock momentum, effectively removes the influence of the market risk premium. The DGTW return adjustment accounts for a large percentage of the cross-sectional variation in asset returns. For instance, we document that the DGTW adjustment captures 85% of the cross-sectional variation of the sample mean returns of our industries (not reported). Furthermore, the DGTW adjustment significantly reduces the variability of momentum strategies, accounting for almost 56% of the individual stock strategy's variation over the sample period, and over 38% of the industry momentum strategy's variation.

However, if industry momentum exists that is unique from individual stock momentum (or drives individual stock momentum) and is not driven by cross-sectional dispersion in mean returns, then employing these past return benchmarks on industry returns should not eliminate industry momentum profits. That is,

$$\begin{aligned} \frac{1}{20}\sum_{I=1}^{20} E[(\tilde{R}^*_{It} - \overline{r}^*_t)(\tilde{R}_{It-1} - \overline{r}_{t-1})] &= \sigma^2_{\mu^*_I} + \sum_{k=1}^{K} \sigma^2_{\beta^*_{Ik}} \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) \\ &+ \sum_{m=1}^{M} \sigma^2_{\theta^*_{Im}} \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1}) > 0, \end{aligned} \tag{13}$$

where $\tilde{R}^*_{It}$ is the industry return composed of a value-weighted sum of $\tilde{r}^*_{jt}$'s for all $j \in I$, $\sigma^2_{\mu^*_I}$

[14] DGTW assign stocks to one of five categories based on the prior period's market capitalization, then within each of these groups divide stocks into five BE/ME categories, and then into five 12 month prior return groups. The breakpoints used for each of the three characteristics are based on NYSE stocks only. Value-weighted returns are then computed for each group of stocks at time t, creating 125 portfolio returns. Each stock is then matched with one of the 125 portfolios based on its characteristics at time $t-1$. The abnormal return for stock j is defined as the return on the stock minus the return on the matched portfolio at time t (i.e., $\tilde{r}_{jt} - \tilde{R}^{b_j,t-1}_t$, where the latter is the month t return of the matched characteristic-based portfolio for stock j). The DGTW, as well as the size and BE/ME adjusted returns, pertain to the Jan., 1973 to July, 1995 time period. The raw return profits correspond to the July, 1963 to July, 1995 time period, but no differences in our results were detected when examining the raw return profits over the Jan., 1973 to July, 1995 time period.

is the cross-sectional variation in mean returns of our value-weighted industry portfolios, once size, BE/ME, and individual stock momentum effects have been accounted for (via DGTW), and $\sigma^2_{\beta^*_{Ik}}$ represents the cross-sectional variation in industry loadings on each of the K factors *after* controlling for size, BE/ME, and individual stock momentum. Thus, $\sigma^2_{\mu^*_I}$ and $\sigma^2_{\beta^*_{Ik}}$ represent the remaining dispersion in mean returns and factor loadings across our 20 value-weighted industries after accounting for size, BE/ME, and individual stock momentum. If these two components are sufficiently small, then only $\sum_{m=1}^{M} \sigma^2_{\theta^*_{Im}} \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1})$ is significantly positive.

Aggregating the individual DGTW-adjusted stock returns, $\tilde{r}^*_{jt}$'s, into industry portfolios, as shown in Table 2 Panel B, the industry momentum profits are still significant, producing average monthly profits of 0.20% (t-stat = 2.27). Thus, individual stock past return benchmarks do not account for industry momentum profits, consistent with industry components generating momentum independent from the momentum in individual stock returns, and possibly contributing to the observed momentum in individual stocks as well. Moreover, the raw industry momentum profit of 0.43% does not significantly differ from the DGTW-adjusted profit of 0.20%, indicating the reduction in mean returns may be a chance event. Also, since the DGTW adjustment is more likely to have long positions in stocks from high momentum industries and short positions in stocks from low momentum industries than a randomly selected portfolio, there already may be a partial industry momentum adjustment built into the DGTW benchmark. Hence, it is not surprising that the DGTW-adjusted industry return is slightly lower than the raw return.

Finally, since raw industry average returns exhibit little variation across industries (see Table 1), and since adjusting industries via DGTW accounts for approximately 85% of this variation, the DGTW industry adjustment provides an even stronger test for whether dispersion in mean returns is responsible for momentum profits. Since industry portfolios also diversify away firm-specific components of returns, only serial covariation in the industry components remains as a possible source of profits. Thus, the existence of industry momentum profits after adjusting for size, BE/ME, and individual stock momentum implies,

$$\frac{1}{20}\sum_{I=1}^{20} E[(\tilde{R}^*_{It})(\tilde{R}_{It-1} - \bar{r}_{t-1})] = \sum_{m=1}^{M} \sigma^2_{\theta^*_{Im}} \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1}) > 0, \tag{14}$$

indicating that serial covariation in industry components is generating significant profits. Remarkably, industry momentum profits are even larger than those reported with the

DGTW adjustment when we risk adjust by subtracting each stock's 32 year sample mean return from its monthly return before applying the portfolio weighting of the industry momentum strategy. Hence, it is unlikely that misspecification of the asset pricing model is driving the industry momentum profitability we are reporting.

4.2.3 Industry Adjusted Profits

Previously, we showed that industry momentum exists after accounting for individual stock momentum. Here, we investigate whether the reverse is true. That is, are there trading profits from individual stock momentum investment after accounting for industry effects? If we subtract each stock's contemporaneous industry return from the stock's own return, and analyze the industry-adjusted return of an individual stock momentum strategy, we obtain profits of sufficiently smaller magnitude. The resulting industry-adjusted 6-month, 6-month individual stock momentum profits are reported in Table 2 Panel A. As the table shows, the profits decline to a marginally significant (t-stat = 2.04) 13 basis points per month, which is largely due to the size effect from the first half of our sample. Thus, when we adjust individual stock returns for size and BE/ME effects, and then subtract the contemporaneous industry return (also adjusted for size and BE/ME effects), we should produce negligible profits. Specifically, these size, BE/ME, and industry adjusted returns are defined as,

$$\tilde{r}_{jt}^{sb,I} \equiv \tilde{r}_{jt}^{sb} - \tilde{R}_{It}^{sb}, \quad \text{for } j \in I \tag{15}$$

where $\tilde{R}_{It}^{sb}$ is the size and BE/ME adjusted return on industry I, to which stock j belongs at time t. The individual stock momentum strategy generates size, BE/ME, and industry-adjusted returns of

$$\frac{1}{N}\sum_{j=1}^{N} E[(\tilde{r}_{jt}^{sb} - \tilde{R}_{It}^{sb})(\tilde{r}_{jt-1} - \overline{r}_{t-1})] = \sum_{k=1}^{K} \sigma_{\beta_k}^2 \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) + \frac{1}{N}\sum_{j=1}^{N} \mathrm{Cov}(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1}). \tag{16}$$

Having previously shown that the first term on the right hand side is zero, matching stocks with industry benchmarks (which accounts for the δ's) thus generates returns that proxy for the last term, the serial covariation in firm-specific components. Table 2 Panel A reports the results for the 6-month, 6-month individual stock momentum trading strategies. As the table shows, momentum in individual stock returns is virtually eliminated when returns are adjusted for industry, size, and BE/ME effects, implying

$$\mathrm{Cov}(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1}) = 0. \tag{17}$$

and indicating that serial covariation in firm-specific return components is not the source of momentum profits, but that industry components seem to be primarily driving momentum.

4.2.4 'Random' Industry Portfolios

To punctuate this point we also analyzed 'random' industry portfolios, replacing every true stock in industry I with another stock that had virtually the same past 6-month return.[15]

Stocks of 'random' industries constructed in this manner will not exhibit momentum if only industry components are truly driving momentum. This is because the cross-sectional variation in $\tilde{\epsilon}$ is much larger than the cross-sectional variation in the industry portfolio $\tilde{\delta}$'s. Therefore, a replacement stock (i.e., a stock with the same past return) is more likely to have had a similar ϵ realization in the past rather than being from the same industry. Thus, since 'random' industries have the same past returns as every true stock in the industry, they will exhibit significant momentum if other components, besides industry, drive momentum. As Table 2 demonstrates, momentum profits are non-existent for the random industries (denoted as $\tilde{R}_{It}^{\spadesuit}$), and momentum profits for individual stocks are virtually unaltered by the random industry adjustment (Panel A), consistent with the *true* industry being the important component behind momentum profits.[16]

[15] Ranking all stocks in ascending order based on their prior 6-month returns, we form 'random' industry portfolios by replacing each stock in an industry with a stock that has the next highest momentum characteristic (6-month prior return) to that stock (and may or may not be in the same industry). In this way, 'random' industry portfolios have the same momentum attributes as the true industry, but contain stocks from various industries. For example, given N stocks ranked in ascending order based on 6-month prior returns, stock j belonging to industry I is replaced with stock $j+1$'s return, for all $j = 1, ..., N$. We obtain virtually identical results if we form 'random' industries by replacing stock j's return with stock $j-1$'s return (i.e., replace each stock with the stock ranked below it). The numbers reported in the table replace stock j's return with an equal-weighted return of the stocks ranked above and below it (i.e., replace $\tilde{r}_{j,t}$ with $\frac{\tilde{r}_{j+1,t}+\tilde{r}_{j-1,t}}{2}$). To avoid endpoint problems, we replace stock N with stock $N-1$ and stock 1 with stock 2.

[16] Grundy and Martin (1998) have claimed that "value-weighting random industry firms highlights errors on the CRSP tapes," [Grundy and Martin (1998, p. 24)] and cite the recorded 1,250% return on Genisco in December of 1994 as an example, where Genisco, a firm with a market capitalization of $383,000, replaced a firm in a 'loser' industry which comprised 9.75% of its industry market capitalization. This they claim drives down the profitability of the random industry momentum strategy since Genisco receives a large negative weight. However, if this one example is driving the low profits on the random industry strategies, then excluding this particular month should significantly alter our findings. It does not, as random industries still do not exhibit profits. Other CRSP errors could only be affecting the profitability of random industry momentum strategies if the errors consistently reduce random industry profits. There is no a priori reason for this to be true. Moreover, the weights assigned to these errors must be larger in the random industries than they are in the true industries. Since we replace every stock in the true industry with a stock ranked above, below, and half a share in each of the stocks ranked above and below it, based on past returns, with no difference in our results, it seems unlikely that such CRSP errors will always be magnified by the random industries. However, to be sure these errors are not driving down the profitability of random industry momentum strategies, we hold the weights of each replacement stock constant, so that CRSP errors have equal importance in both the true and random industries. Thus, Genisco receives the same weight in the

4.2.5 Industry Neutral Portfolios

Finally, we create three zero-cost portfolios as alternative specifications for documenting the importance of industry momentum. The first portfolio is formed as follows: for each industry, stocks are first sorted on past 6-month returns, and the value-weighted average return of the top 30% of stocks minus the bottom 30% of stocks *within the industry* is computed at time t and held for six months (i.e., a 6-month, 6-month strategy). We refer to this portfolio as an 'industry neutral' portfolio, since low past return stocks are subtracted from high past return stocks within the same industry. As Table 2 demonstrates, the industry neutral portfolio produces mean profits of 0.0011 with an insignificant test statistic of 1.01, indicating, again, that once we account for industry effects, momentum in individual equities is virtually non-existent.

For the second portfolio, stocks are ranked globally based on their past 6-month return in excess of their industry average over the same time period. The equal-weighted average return of the top 30% of stocks minus the bottom 30% based on the excess return ranking is computed at time t (and held for 6 months). We refer to the second portfolio as an 'excess industry' portfolio, since we select our winning and losing stocks based on their past returns in excess of the industry benchmark. As Table 2 shows, the excess industry portfolio does not exhibit significant profits (mean = -0.0007, t-stat = -0.83), consistent with industry components being a primary source of momentum.

The third portfolio is long the losing stocks from the winning industries, and short the winners from the losing industries. Conditional on being in the three industries which performed the best over the last 6 months, we rank stocks within each of these industries based on their prior 6-month returns and form a value-weighted portfolio of the *bottom* 30% of stocks within each of these three high past performing industries. Likewise, we form a value-weighted portfolio of the *top* 30% of past 6-month return stocks belonging to each of the three worst performing industries, and subtract this portfolio return from the previous one. This zero-cost portfolio should exhibit significant profits if industry effects drive momentum profitability, and should produce significant *negative* profits if individual stock returns are the primary source of momentum profits. As Table 2 shows, this portfolio produces positive and significant profits of 0.30% per month, indicating the importance of

random industry as it does in its true industry. The results using these 'true' weights, however, are unaltered, as random industry momentum strategies still fail to produce profits.

industries in generating momentum profits.

5 Robustness of Industry Momentum Strategies

Previously, we have used a variety of methods to document that individual stock momentum strategies are generating large returns because of the profitability of industry momentum strategies. The analysis focused on the buying and selling of stocks and industry portfolios based on their past 6-month returns. We also focused exclusively on stock and industry momentum portfolios which were held for 6 months. This section analyzes whether this strong industry momentum effect exists at other horizons as well.

Ranking the 20 industries based on their $L(= 1, 3, 6, 9, 12, 24)$-month lagged returns, we form portfolios of the highest and lowest past performing industries, holding them for $H(= 1, 6, 12, 24, 36)$ months, rebalancing monthly. Three sets of industry momentum trading strategies are employed: **IMS1** merely invests in the highest past return industry and shorts the lowest past return industry; **IMS2** computes the equal-weighted return of the three highest past return industries and subtracts the equal-weighted return of the three lowest past return industries; and **IMS3** computes the equal-weighted return of all industries with past returns greater than the cross-sectional mean prior L month return and subtracts the equal-weighted return of all industries with past returns less than the average prior return. The results from the industry momentum trading strategies are plotted in Figure 1.

The three industry momentum strategies all produce similar patterns in returns. IMS1 generates the highest mean returns over intermediate investment horizons (3-12 months), and lowest mean returns over longer horizons (24 and 36 months). As we include more industries in our 'winning' and 'losing' portfolios, via strategies IMS2 and IMS3, the profits from the zero-cost portfolios decline, but still are strong. The magnitude of these profits suggests that momentum in industries is not driven by just the three highest and three lowest past performing industries.

The results are also consistent with the findings of Jegadeesh and Titman (1993) for individual stock returns, where momentum profits are strong over intermediate holding periods (3-12 months), but diminish beyond a year. The negative returns from the $L = 24$, $H = 36$ month strategy are consistent with the findings of DeBondt and Thaler (1985),

who document long-run (3-5 year) negative autocorrelation in returns for individual stocks. However, it seems that only the extreme industries (IMS1) exhibit these long-run reversals. IMS2 exhibits marginally negative profits while IMS3 does not exhibit any significant reversal. This is also consistent with DeBondt and Thaler (1985), who find that long-term reversals are concentrated in the most extreme securities.

5.1 Trading Frictions and Lead Lag Effects

For the sake of brevity, the remainder of this paper focuses on IMS2 strategies of various horizons for both the ranking period and the holding period. A breakdown of the IMS2 strategies for various ranking periods and horizons is provided in Table 3, which reports the $L = 1, 6, 12$, and $H = 1, 6, 2, 24, 36$ month strategies. The table reports the winners minus losers (Wi-Lo) profits as well as the winners minus middle three industries (Wi-Mid) and middle minus losers (Mid-Lo) profits, to gauge whether industry momentum profits are largely driven on the buy side (long positions) or sell side (short positions).

Industry momentum strategies that rank on six months and hold for six months, which we focused on earlier, require turnover of approximately 200% per year. Breakeven transaction costs are therefore approximately 75 basis points per dollar of one-way long or short transaction. Consistent with the results on individual stock momentum, Table 3 shows that holding onto the long and short positions for an additional six months beyond the initial six-month holding period (using the original six month ranking period) does not reduce the average monthly return. Thus, it is possible to reduce turnover to 100% per year, raising the breakeven one-way transaction cost per dollar to 150 basis points per dollar of one-way long or short transaction. Since the strategy employs value weights within the industry, the trading costs associated with large and mid-cap firms apply more than those for small firms. The 150 basis point breakeven transaction cost appears to exceed the actual transaction costs that institutional traders we have talked to typically estimate for mid-cap and large cap stocks (bid-ask spread, commissions, plus market impact). However, the returns of stocks within extreme winning and losing industries may be more volatile than those within less extreme industries, temporarily raising the trading costs for stocks when it is desirable to employ them in an industry momentum strategy. Thus, we believe that the profitability of industry momentum strategies after actual trading costs is a subject for future research.

Short sales constraints may also hinder an industry momentum strategy. Not all stocks are easily borrowed for a short sale. In contrast to an individual stock momentum strategy, where it is short positions that appear to contribute to the bulk of the strategy's profitability, the profitability of the industry momentum strategy explored here is mostly due to the long side of the position. A strategy that is long the highest three momentum industries and short the middle three momentum industries, as ranked on the prior six months and held for six months, exhibits an average monthly return of 0.36%, while the middle three industries exceed the bottom three momentum-ranked industries by an average of 0.07% per month, as shown in Table 3. Thus, industry momentum strategies appear to profit mostly on the buy side, making them less susceptible to short sales constraints, and therefore potentially more feasible to implement.

In addition, prior research, as found for example in Lo and MacKinlay (1990) and Jegadeesh and Titman (1995b), has shown that stock portfolios can exhibit positive serial correlation due to lead-lag effects that are associated with firm size. Some of this is due to thin trading in small stocks, however, at longer horizons than a day, it is due to small firm returns being correlated with the large firms' returns that occurred many days and weeks earlier. This effect is strongest at shorter horizons. Earlier, we argued that the consecutive months between the ranking period and the holding period could only negligibly affect the magnitude of an individual stock momentum strategy since our 6-month, 6-month strategy only places a 1/6 weighting on the ranking period closest to the investment period. The same is true for industry momentum. However, for robustness, we skip a month between the ranking period and holding period in Table 3 Panel B. As the table shows, the data seems to support our assertion. Lagging the ranking period by one month, and implementing the analogous momentum strategy, the average monthly return is 0.40% (shown in Table 3 Panel B), which negligibly differs from the 0.43% per month average return for industry momentum reported in Table 3 Panel A (which does not skip a month).

Some researchers, notably Grundy and Martin (1998), have argued that industry momentum may be due to lead-lag effects that are not due to size. This is almost tautological. If, indeed, individual stock momentum does not exist intra industry, as Table 2 Panel C indicates, industry momentum has to be a lead-lag effect between stocks within the industry. It may be that researchers can identify a variable that sheds more light on this lead lag effect. However, to date, no such variable has been found. More importantly, this effect

is only of concern if it prohibits profitable trading. For instance, if such an effect is due to bid-ask bounce or liquidity, then this may severely limit our ability to profit from these strategies. We will address these issues shortly and demonstrate that neither of these effects significantly influences our results.

Looking across the rows of Table 3 for each of the strategies under Panels A and B, one interesting regularity is that the buy side profits decline rapidly and generally disappear after 12 months, eventually becoming negative (reversing) at 24 and 36 months. However, the sell side profits diminish less rapidly, and tend not to reverse at 24 or even 36 months. This phenomenon may be due to the fact that it is typically more difficult for investors to short assets, and therefore arbitrage away momentum on the downside. This asymmetry may also be consistent with some of the conjectures in Hong, Lim, and Stein (1998) pertaining to analyst coverage and the desire for analysts to withhold bad information.

Finally, Table 3 reports the profits for various L,H momentum strategies adjusting returns for size, BE/ME, and *individual stock momentum* effects via DGTW.[17] As the table shows, the industry momentum strategies remain substantially profitable, further indicating that industry momentum is stronger than and seems to dominate individual stock momentum.[18]

5.2 The One-Month One-Month Industry Momentum Trading Strategy

As Table 3 indicates, the strongest industry momentum strategy is the 1-month lagged, 1-month holding period strategy, both raw and adjusting for risk with the DGTW method. In contrast to the 6-month, 6-month industry momentum strategy, where the long positions generate most of the profit, the profitability of the 1-month, 1-month industry momentum strategy appears to be equally driven by the long and the short sides of the position.[19] Also in contrast to the 6-month, 6-month strategy, the 1-month, 1-month strategy's 1200% turnover ratio would seem to preclude profits after transaction costs, despite its significantly

[17] In addition, we regressed these DGTW-adjusted profits on the Carhart (1997) factors in order to account for any potential remaining effects of size, BE/ME, or individual stock momentum. The results were nearly identical.

[18] As discussed earlier, to control for a component to expected returns that might be missing, which is not being captured by the DGTW adjustment, we also "demean" the industry returns by subtracting off their sample mean over the entire 32 year period. The results (not reported) were unchanged, as industry momentum remained highly profitable.

[19] The sell side generates most of the 1-month, 1-month profitability when we skip a month between portfolio formation and holding period.

higher average return. However, even with large transactions costs, this finding is still of extreme interest for those wishing to understand asset pricing in the context of the momentum anomaly.

The strength of the 1-month, 1-month strategy is surprising given the findings of Jegadeesh (1990), who documents short-term return reversals in individual stocks. Thus, whereas individual stock momentum for the 6-month, 6-month strategy is closely linked to the profitability of an industry 6-month, 6-month strategy, the one-month serial correlation for individual stocks appears to be of the opposite sign of the one-month serial correlation for industries. One possible explanation for the discrepancy between short-term (1 month) reversals for individual stocks and short-term continuation for industries is that the one month return reversal for individual stocks is generated by microstructure effects (such as bid-ask bounce and liquidity effects), which are alleviated by forming industry portfolios.

To analyze this hypothesis, we skip a month before computing the 1-month holding period returns, so that industries and stocks are selected based on their prior returns from the end of month $t-3$ to $t-2$, while holding period returns are computed in month t. industry momentum persists and is quite strong, producing mean raw profits of 0.71% (t-stat = 3.66), and DGTW adjusted profits of 0.57% per month (t-stat = 3.33). Reversal effects for individual stocks (not reported for brevity) are no longer prevalent, however, as the strategy produces positive, not negative, profits of 0.25% (t-stat = 1.41). Thus, microstructure effects may be partly responsible for the short-term reversal effect in individual stocks,[20] although Jegadeesh (1990) finds that such effects do not explain the short-term reversal effect entirely.

The magnitude of the profits from 1-month, 1-month industry momentum strategies also refutes the Conrad and Kaul (1998) assertion that it is the statistical relation between sample means and true means that drives the profitability of momentum. The dispersion in ex-ante means in any 1-month sorting is much smaller than that in a 6-month sort, yet the profits of the 1-month strategy are much higher. Table 4, for example, reports summary statistics on the IMS2(1,1) trading strategy and documents that it is a broad-based phenomenon. As the table shows, the most any industry appeared in the winners category was 80 months (Food & Beverage) out of a possible 347, or 23% of the time.

[20] Asness (1995) also finds that the short-term reversal effect in individual stock returns is attenuated when examining the largest, most liquid stocks. This is consistent with microstructure and liquidity effects influencing the profitability of short-term strategies. For further discussion of these issues, see Conrad and Kaul (1989), Jegadeesh and Titman (1995a), Kaul and Nimalendran (1990), and Lo and MacKinlay (1990).

Likewise, the most any industry appeared in the losers category was 83 months (Fabricated Metals). In addition, the maximum number of *consecutive* months an industry appeared in either the winners or the losers portfolio was five. Thus, neither the winners or losers portfolios seem to be dominated by a particular industry. In fact, the average rank of each industry only ranged from 10.01 to 10.96, further indicating that certain industries are not more likely to be classified as winners or losers than others.

If Conrad and Kaul (1998) are correct, and the dispersion in mean industry returns is what drives momentum profits, then industries with higher (lower) mean returns should be classified as winners (losers) more often than other industries. This does not appear to be the case from the first three columns of Table 4. Furthermore, referring to Table 1, there appears to be little relation between the sample mean returns of the industries and the frequency with which they appeared in the winners and losers categories. For example, of the five highest sample mean return industries (Food & Beverage, Petroleum, Manufacturing, Railroads, and Retail), only two (Food & Beverage and Petroleum) appeared in the winners portfolio more often than the average industry, and only two (Food & Beverage and Retail) appeared in the winners portfolio more often than they did in the losers portfolio. The low correlations between the rank of each industry at month t and its rank in the previous month, reported in column 4 of Table 4, further indicate that the winners and losers are not dominated by the same industries and that cross-sectional dispersion in mean returns, which should induce high correlation between rankings from one period to another, is unlikely driving momentum profits.

Finally, profits from the 1-month, 1-month strategy are even larger than those reported with the DGTW adjustment when we risk-adjust returns by subtracting each stock's 32-year sample mean return from its monthly return before applying the portfolio weighting from the strategy. Hence, it is unlikely that misspecification of the asset pricing model is driving the industry momentum profitability we are reporting.

Table 4 also reports the partial autocorrelation coefficients of our industries at 1, 6, 12, and 36 month lags. As the table shows, the partial autocorrelation coefficients are consistent with the patterns reported for industry momentum profits: There is strong persistence in the short-term that dissipates and eventually reverses.

5.3 The Lead-Lag Effect and 1-Month, 1-Month Industry Momentum

In contrast to the longer term industry momentum analyzed earlier, the remarkably strong 1-month industry momentum effect may be exaggerated by the lead-lag effect. In the last subsection, we learned that skipping a month reduces the profitability of the 1-month, 1-month industry momentum strategy by about 33% (from 105 to 71 basis points per month). One explanation for this reduction in profitability is that skipping a month eliminates market microstructure effects. In this subsection, we present evidence that this is not the case. The reduction in profitability arising from skipping a month is simply because the more distant ranking period appears to be less salient to investors.

The thrust of our argument here is that industry portfolios are value-weighted, and thus largely alleviate lead-lag effects associated with firm size or volume (a proxy for liquidity). To quantify the impact of the lead lag effect, at time t we select the three industries which performed the best and the three which performed the worst over the period ending month $t-3$ to the end of month $t-2$ (i.e., skip a month). Then, within each industry, we sort stocks into quintiles based on their market capitalization at time $t-2$. Instead of computing the return of the three highest past performing industries minus the three lowest past performing industries, we now compute the average return of the highest size quintiles within each of the three highest past performing industries, and subtract the average return of the highest size quintiles within each of the three lowest past performing industries. That is, we restrict securities to only the largest 20% of stocks within *each industry*. These stocks are then value-weighted so that their weights sum to one. If lead-lag effects are primarily driving the 1-month, 1-month industry momentum profits, then skipping a month *and* restricting the industries to contain only the largest stocks should produce significantly reduced profits.

As Panel A of Table 5 shows, the 1-month, 1-month momentum profits for the largest stocks, skipping a month, are 0.77% per month when securities are value-weighted within industries, and are of the same order of magnitude as the IMS2(1,1) profits reported previously, which employ all stocks in the industry. This suggests that lead-lag effects are not materially affecting the reported profits.

This does not mean that the lead-lag effect has mysteriously disappeared from our data. Notice that restricting securities to belong to the *smallest* 20% of stocks within each industry, we find that profits substantially increase (as shown in Table 5 Panel A),

indicating that a significant lead-lag relation based on small firms following the lead of large firms may be present. As Table 5 shows, the DGTW-adjusted profits still exhibit a substantial discrepancy between large and small stock profits, and thus, the discrepancy is probably due to a lead-lag effect rather than a size premium.

However, because of value weighting, the impact of this lead-lag effect on the IMS2(1,1) profits is minimal. Panel B of Table 5 decomposes the profits from the IMS2(1,1) strategy into size quintiles as described above. Specifically, we restrict industries to only contain stocks within a particular size quintile, and compute the profits assuming the holding period returns are only computed from stocks within that particular size category. As before, the winning and losing industries are still chosen based on the entire industry return in the previous period (again, skipping a month between the formation and holding periods), so that the same industries are selected for our IMS2 strategy. The difference here is that we do not rebalance stocks within each quintile to sum to one, so that we can capture the contribution of each size category to total profits. As Table 5 demonstrates, the smallest stocks contribute only 1.19% to total value-weighted profits, while the largest stocks generate nearly 70% of these profits. Controlling for size, BE/ME, and individual stock momentum via the DGTW return adjustment procedure, the picture is even more clear, as the size premium no longer confounds the influence of small stocks, and, not surprisingly, the contribution of small stocks to adjusted profits is even smaller, at only 0.59%, while the largest stocks contribute 77.58% of the profits. This result is not surprising since stocks within an industry are value-weighted, and reconfirms our earlier conjecture that value-weighting largely alleviates the impact of lead-lag effects on profits.[21]

Of course, size is only a proxy for a potential lead-lag relation among actively traded and illiquid stocks. We therefore verify that the results above apply when we sort on dollar trading volume ($Vol at time $t-2$) instead of size. Table 5 reports the raw and DGTW-adjusted industry momentum profits for the largest and smallest trading volume stocks, employing value-weighted industries, and skipping a month between the portfolio formation and holding period. As the table shows, the largest dollar trading volume stocks generate *more* profits than the smallest $Vol stocks. Likewise, when we decompose the

[21] We also ran these tests equal-weighting the stocks in each industry and controlling for size. Not surprisingly, the influence of small stocks, and hence lead-lag effects, were more pronounced when equal-weighting was employed, but the magnitude of this influence was still too small to explain any significant portion of momentum profits.

IMS2(1,1) profits into dollar volume quintiles in Panel B, most of the trading profits come from the largest, most liquid stocks. Thus, if dollar trading volume provides a reasonable measure of liquidity, then a lead-lag relation tied to liquidity within industries does not appear to be affecting the profits. Moreover, if one wishes to exploit industry momentum, it seems that the most liquid stocks provide the greatest opportunities.[22]

The final piece of evidence about the lead-lag relation comes from the random industries discussed earlier. If a lead-lag relation was driving their profits, they should exhibit spurious momentum for a 1-month, 1-month strategy. However, the random industries do not exhibit 1-month, 1-month momentum profits. Thus, a liquidity-related lead-lag relation is a dubious explanation for our findings.

6 Fama-MacBeth Regressions

This section addresses the generalizability of our results by running Fama and MacBeth (1973) cross-sectional regressions for various individual and industry momentum strategies. This analysis provides a robustness check on our results, since the regressions employ all securities (i.e., no breakpoint specification is needed). The regressions also allow us to control for potentially confounding microstructure factors, examine the interaction between different momentum horizons simultaneously, and avoid weighting stocks based on size.

6.1 The Cross-Section of Expected returns

This subsection employs Fama and MacBeth (1973) cross-sectional regressions at each point in time on the universe of securities to determine how various industry momentum strategies interact with various individual stock momentum strategies and market microstructure effects to explain size and book-to-market adjusted returns of stocks. Specifically, we regress the cross-section of stock returns, characteristically adjusted for size and BE/ME effects (with the Daniel and Titman (1997) procedure described earlier in the paper), at time t on a constant and a host of firm characteristics. The reason for employing the cross-section of size and BE/ME adjusted returns, rather than simply the raw returns, is to control for these potentially confounding effects in order to isolate the momentum anomaly. Previous

[22] Asness and Stevens (1996) also document a strong 1-month industry momentum effect among 49 industries using 4 digit SIC codes, and show that this strategy remains significant even when they restrict the sample to the largest, most liquid stocks.

evidence in the paper indicates that momentum profits are affected by the size premium. Also, Lakonishok, Shleifer, and Vishny (1994) showed that BE/ME and momentum are correlated. Thus, we adjust returns for these two effects by subtracting the returns of matched characteristic portfolios. In addition, we include size and BE/ME attributes as regressors, in order to more fully purge the cross-section from any confounding influences. In addition, the use of characteristic-adjusted returns eliminates cross-sectional dispersion related to market β's (as noted earlier in Section 4.2.1), and thus mitigates concerns of estimating betas in order to account for market effects on the cross-section.

The first set of independent variables include: market β,[23] size (log of market capitalization at $t-1$), BE/ME (book value plus deferred taxes and investment tax credits divided by market capitalization, from the previous period), and the prior six month return of the stock $ret_{-6:-1}$ (the average return from $t-6$ to $t-1$). The next regression simply adds the past one month return, $ret_{-1:-1}$, and the return from $t-36$ to $t-13$, $ret_{-36:-13}$, of each individual stock. The coefficients from these regressions are then averaged over time and reported in Table 6, along with their time-series t-statistics. The results from these regressions confirm previous findings and provide a benchmark for other regressions. The one month return controls for liquidity and microstructure effects documented by Jegadeesh (1990) that induce a reversal in short-term individual stock returns. Thus, $ret_{-6:-1}$ becomes significant once this effect is accounted for. The long-run return captures the DeBondt and Thaler (1985) 3-5 year reversal effect, attempting to magnify it by skipping the nearest year of returns (which we know generates a continuation rather than a reversal).

These regressions are repeated for three other intermediate horizon momentum variables. For completeness we also examine the (6,6) strategy, the (12,1) strategy, analyzed by Grundy and Martin (1998), Carhart (1997), and Fama and French (1996), and the (12,12) strategy, which we employ for robustness (and is also analyzed in Jegadeesh and Titman (1993)). Incorporating the (12,1) strategy entails replacing $ret_{-6:-1}$ with $ret_{-12:-1}$ in each

[23] Market β's are estimated by regressing the prior 36 months of excess returns for each stock on a constant and the past 36 months of excess returns of the CRSP value-weighted index. Stocks are then ranked based on their coefficient estimates from this regression (pre-ranking betas) and assigned to one of 100 groups based on this ranking. Stocks within a particular beta group are assigned the (equal-weighted) average beta for that group. This is similar to the procedure employed in Fama and French (1992), except that we do not assign post-ranking betas. However, we ran it both ways and did not alter our findings. This procedure is employed to mitigate the errors-in-variables problem inherent in beta estimates. Also, since our dependent variable is the cross-section of size, and BE/ME *adjusted* returns (which account for the market risk premium), the errors-in-variables problem for beta is less of an issue.

of the previous regressions. Accomodating the (6,6) and (12,12) strategies is more complex, since these strategies are themselves equal-weighted averages of six and twelve strategies, respectively. However, we replace $ret_{-6:-1}$ with $ret_{-6:+6}$, which is simply the equal-weighted average of the returns from $t-11$ to $t-6$, . . ., $t-6$ to $t-1$:

$$ret_{-6:+6} = \frac{ret_{-11:-6} + \ldots + ret_{-6:-1}}{6}.$$

$ret_{-12:+12}$ is defined similarly.

The evidence in Table 6 Panel A reaffirms previous findings in the literature: There is a strong short-term (1-month) reversal effect, intermediate-term momentum effect, and a somewhat weaker long-term reversal effect in individual stocks, none of which seem to explain the other, which may cast doubt on theories which link these various anomalies. However, while $ret_{-36:-13}$ appears statistically significant, its economic significance is small.[24] Both the (6,1) and (12,1) momentum variables are confounded by the one month reversal effect, making these variables insignificant. However, adding $ret_{-1:-1}$ to the regressions controls for this effect and increases their significance. Note also that the (6,6) and (12,12) strategies are unaffected by the 1-month return, confirming our previous intuition that these strategies are uncontaminated by any potential short-term effects due to microstructure or liquidity, and casting doubt on the claims made by Grundy and Martin (1998). However, since the (12,12) effect incorporates returns up to two years past, this variable is confounded by the long-run reversal effect. Thus, when the long-term stock return is included as a regressor, the (12,12) strategy becomes significant.

We also ran the same cross-sectional regressions using industry momentum variables by replacing $ret_{-L:-H}$ with $ind_{-L:-H}$, which is the industry return over the (L, H) time period to which each stock belongs. The regression results confirm previous findings in the paper: There is a strong short-term (1-month) *momentum* effect in industries, a strong intermediate-term momentum effect, and a statistically insignificant long-term reversal effect, although its economic significance is as large as that for individual stocks. More telling, is the interaction between the short-term and intermediate-term industry momentum variables. For instance, $ind_{-6:-1}$ and $ind_{-12:-1}$, which are highly significant in the first regressions (t-stats = 5.48 and 5.80, respectively), appear to be significantly reduced by $ind_{-1:-1}$. Thus, the significance of the (6,1) and (12,1) industry strategies are partly due

[24] This may be sample specific, since the DeBondt and Thaler (1985) long-run reversal effect is weak over the 1963-1995 time period.

to the strength of the 1-month effect. Finally, the (12,12) strategy is initially marginally insignificant, and is then weakened substantially by controlling for the 1-month industry momentum effect. However, the (12,12) strategy becomes significant once we control for the long-term reversal effect by including $ind_{-36:-13}$.

Finally, we combine the individual stock and industry past return or momentum variables in the same regression to analyze the interaction between them for the cross-section of expected stock returns. The results in Table 6 Panel C show that industry momentum at 6 months subsumes individual stock momentum at 6 months, for both the (6,1) and (6,6) strategies. This is consistent with previous evidence in the paper. Furthermore, the 1-month industry momentum variable substantially reduces the industry 6-month variable. Hence, 1-month industry momentum also drives a significant portion of 6-month individual stock momentum, as the regressions indicate. Examining the interaction between the (12,1) strategies, however, we find that although $ind_{-12:-1}$ weakens the influence of $ret_{-12:-1}$, and $ind_{-1:-1}$ weakens each of these in turn, all of these variables continue to remain significant. Thus, the one year horizon continues to remain important for both industry and individual stock momentum. Therefore, several horizons seem to be of most interest to investors regarding industry momentum: The past 1-month, 6-month, and 12-month return of the industry, but only one horizon seems to have importance for individual stock momentum: The past one year return of the individual stock itself.

Finally, Grundy and Martin (1998) claim that industry momentum is driven by lead-lag effects. Our previous regressions controlled for 1-month individual stock return and industry return effects by including these variables as regressors. Alternatively, we could also skip a month between the formation and holding period (as Grundy and Martin (1998) do), for all past return variables. The regressions in Panel C are rerun for the interaction between individual and industry momentum variables, where $ret_{-6:+6}$ and $ind_{-6:+6}$ become an equal-weighted average of *five* past return strategies (i.e., excluding the return from $t-6$ to $t-1$). The results are reported in Panel D of Table 6. They demonstrate absolutely no difference in our findings: $ret_{-7:-2}$ is subsumed by $ind_{-7:-2}$, the (6,6) strategy is subsumed by the industry (6,6) strategy, and the (12,12) strategy is subsumed by the industry (12,12) strategy. Thus, again, the only strategy which retains any significance for individual stock momentum is the (12,1) strategy (in this case (13,2) since we skip a month).

Thus, the issues raised by Grundy and Martin (1998) do not seem to be affecting our results, and the only individual stock momentum variable of any significance (among four different strategies) is the 12-month strategy. However, none of the industry momentum variables are subsumed by individual stock momentum, despite the fact that skipping a month tends to strengthen individual stock momentum and weaken industry momentum. Nor does industry momentum seem to be driven by lead-lag or microstructure effects. Finally, while the existence of 12-month individual stock momentum is noteworthy, it is of less importance if it is a seasonal effect. Grinblatt and Moskowitz (1998) claim that the (12,1) individual stock momentum strategy's profitability is probably due to tax loss selling at the end of the year.

7 Conclusion

We find a strong and persistent industry momentum effect that does not appear to be explained by microstructure effects, individual stock momentum, or the cross-sectional dispersion in mean returns. Furthermore, industry momentum appears to be contributing substantially to the profitability of individual stock momentum strategies, and, except for 12-month individual stock momentum, captures these profits entirely. These findings are robust to several specifications and treatments and offer important practical insights on the profitability of momentum investment. Specifically, while the existence of individual stock momentum documented by Jegadeesh and Titman (1993) seemed to offer a near arbitrage opportunity for rational investors (by buying a well-diversified portfolio of winners and selling a well-diversified portfolio of losers, with identical factor exposures), the results in this paper indicate that such strategies are, in fact, not well diversified, since the winners and losers tend to be from the same industry. Moreover, if one were to trade on momentum, industry momentum appears to be the proper choice, offering a 'good deal' to rational investors, but far from an arbitrage.

The robustness of industry momentum is impressive. Industry momentum is never subsumed by individual stock momentum and consistently dominates individual stock momentum at every horizon except the (12,1) strategy. In addition, industry momentum generates as much of its profits on the buy side as it does the sell side, unlike individual stock momentum strategies which seem to be driven mostly on the sell side, and appears

to remain strong among the largest most liquid stocks. Thus, industry momentum strategies may have lower transactions costs and are less susceptible to short sales constraints than individual stock momentum strategies, making their practical implementability more feasible and less costly.

These results may offer new insights on the role of industries in the international economy. Recently, Rouwenhorst (1997) documents that momentum strategies are highly profitable in Europe, yet Wo (1997) finds that momentum is non-existent in Japan. Since the industrial structure of the U.S. is similar to that of Europe, but quite different from that of Japan, industry influences may play a vital role in this discrepancy. Evaluating the influence of industry momentum in foreign markets is thus a natural extension of this study, and will provide an out of sample test for many of the conjectures in this paper.

This paper may add confusion to an already puzzling list of empirical evidence on momentum. We find that industry momentum is important over many horizons, while the only horizon for which individual stock momentum is present is at 12 months. However, the strength of the one month industry effect casts doubt on recent behavioral theories for the momentum anomaly, which have focused on linking the short-term, intermediate-term, and long-term individual stock momentum results documented in a variety of investor behavioral patterns and cognitive biases.[25]

The pattern of momentum profitability is not yet well understood, and may be confounded by signal-to-noise issues associated with the ranking procedures. For instance, at shorter horizons the dispersion in idiosyncratic components of individual stock returns is likely to dominate all other return components. Thus, ranking stocks based on their past raw returns essentially ranks them according to firm-specific noise at short horizons. Conversely, ranking stocks on intermediate horizon returns (6-12 months) likely smooths idiosyncratic noise and may provide a better measure of the industry component of returns. Hence, individual stock momentum profits may not be present at short horizons, but will begin to appear as the sorting period used to rank stocks lengthens, providing a proxy for industry momentum, because the sorting procedure is less polluted by noise at long horizons. Therefore, individual stock momentum can be present and stronger at intermediate horizons even if a simple AR(1) process for industry return components were to exist, yet

[25]See, for example, Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1998).

no autocorrelation in firm-specific components existed.

Sorting on even longer horizon returns should reduce idiosyncratic noise further. Thus, it seems odd that at 3-5 year horizons, both industry momentum and individual stock momentum profits tend to reverse. One possibility is that at long horizons, both the idiosyncratic component and industry component of returns are smoothed, and that one obtains a more precise measure of the time-varying (conditional) mean return of stocks (and industries). If this is the case, then these mean returns seem to exhibit slow mean reversion over time. Alternatively, the return generating process may follow some sort of moving average process in conjunction with an autoregressive dynamic. In any case, such return dynamics offer alternative explanations for the patterns in momentum profits. Our point is that these patterns are not yet well understood, and even a simple AR(1) process in industry components raises some interesting methodological issues that may confound our understanding of momentum and other return-based trading patterns. We leave a deeper exploration of these issues for future research.

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Table 1: Description and Summary Statistics of Industries

Summary statistics of our 20 industry portfolios are reported below, including the two digit SIC code groupings used to form our industries. The industries are formed monthly, from July, 1963 - July, 1995 using CRSP SIC codes, which allow for time-variation in industrial classification. The average number of stocks assigned to each industry portfolio every month are reported, along with the minimum number of stocks appearing in each portfolio at any point in time (reported in parentheses). In addition, the average percent of total market capitalization, average return in excess of the three month Treasury Bill rate, standard deviation, and average abnormal return in excess of size and BE/ME matched benchmarks (t-stats in parentheses) of each industry over the sample period are reported below, as well as the cross-sectional averages of these statistics across the industries reported at the bottom of the table. We also report the Gibbons, Ross, and Shanken (1989) F-stat for whether the mean returns and abnormal returns are significantly different from zero, as well as an F-stat that the returns are equal across industries (with p-values in parentheses). The size and BE/ME adjusted returns correspond to the Jan., 1973 to July, 1995 time period.

	Industry	SIC Codes	Avg. No. Stocks†	Avg. % of Market Cap.	Excess returns	Abnormal returns	(t-stat)
1.	Mining	10-14	279.86 (123)	4.50%	0.0040	0.0002	(0.07)
2.	Food	20	126.89 (100)	4.53%	0.0065	0.0036	(2.70)
3.	Apparel	22-3	117.03 (84)	0.67%	0.0046	0.0004	(0.19)
4.	Paper	26	53.21 (41)	2.32%	0.0047	0.0015	(0.87)
5.	Chemical	28	208.15 (126)	9.85%	0.0047	0.0016	(1.26)
6.	Petroleum	29	37.49 (26)	8.94%	0.0055	0.0025	(1.52)
7.	Construction	32	56.44 (39)	0.96%	0.0047	0.0008	(0.46)
8.	Prim. Metals	33	85.11 (66)	1.95%	0.0020	-0.0010	(-0.42)
9.	Fab. Metals	34	119.38 (76)	1.21%	0.0054	0.0020	(1.60)
10.	Machinery	35	274.16 (143)	7.38%	0.0030	-0.0008	(-0.56)
11.	Electrical Eq.	36	311.60 (165)	5.57%	0.0049	0.0023	(1.38)
12.	Transport Eq.	37	105.35 (91)	5.01%	0.0043	0.0019	(1.05)
13.	Manufacturing	38-9	235.21 (70)	4.05%	0.0055	-0.0006	(-0.43)
14.	Railroads	40	20.11 (9)	0.81%	0.0055	0.0035	(1.38)
15.	Other Transport.	41-7	88.03 (51)	1.19%	0.0040	-0.0011	(-0.47)
16.	Utilities	49	187.08 (114)	7.52%	0.0027	-0.0000	(-0.03)
17.	Dept. Stores	53	54.79 (36)	2.89%	0.0051	0.0014	(0.64)
18.	retail	50-2, 54-9	377.06 (143)	3.34%	0.0055	0.0021	(1.41)
19.	Financial	60-9	891.56 (152)	12.42%	0.0045	0.0007	(0.54)
20.	Other	other	981.18 (221)	14.90%	0.0046	0.0019	(1.96)
	Average		230.48 (93.80)	5.00%	0.0043	0.0011	(1.35)
	GRS F-stat				2.920	1.686	
	(p-value)				(0.000)	(0.034)	
	F-stat				0.825	1.38	
	(p-value)				(0.677)	(0.136)	

† Minimum number of stocks in parentheses.

The Bonferroni-adjusted critical values at the 5% and 1% level are 3.10 and 3.34, respectively.

Table 3: Industry Momentum Trading Profits

Average monthly profits of the industry momentum trading strategies over the July, 1963 - July, 1995 time period (i.e., T=383) are reported below. The industry momentum portfolios are formed based on L-month lagged returns and held for H months. Results are reported for the **IMS2(L,H)** industry momentum trading strategy, where the winners portfolio is the equal-weighted return of the highest three momentum industries, the middle portfolio is the equal-weighted return of the middle three momentum industries, and the losers portfolio is the equal-weighted return of the lowest three momentum industries. The returns for the winners (Wi), losers (Lo), and winners minus losers (Wi-Lo), are reported, as well as the winners minus middle (Wi-Mid), and middle minus losers (Mid-Lo), where the 'middle' portfolio is the equal-weighted average return of the three industries ranked 9, 10, and 11 based on past L-month sorts. T-statistics for the zero-cost strategies are in parentheses. For brevity, we only report the $L = 1, 6, 12$-month lagged and $H = 1, 6, 12, 24, 36$ month holding period strategies. Panel A reports the profits when no gap exists between the portfolio formation period and the holding period (i.e., sort on $t - L$ to $t - 1$ returns). Panel B skips a month between the portfolio formation and holding periods (i.e., sort on $t - L - 1$ to $t - 2$ returns). Finally, both panels report the DGTW-adjusted Wi-Lo profits, which controls for size, BE/ME, and individual stock momentum effects, and pertain to the Jan., 1973 to July, 1995 time period.

		IMS2 Industry Momentum Trading Strategies									
		Panel A:					**Panel B: *Skip a Month***				
L	$H =$	1	6	12	24	36	1	6	12	24	36
1	Wi	0.0193	0.0140	0.0143	0.0137	0.0138	0.0144	0.0135	0.0142	0.0134	0.0137
	Lo	0.0088	0.0118	0.0112	0.0122	0.0130	0.0073	0.0116	0.0110	0.0125	0.0131
	Wi-Lo	0.0105	0.0022	0.0032	0.0015	0.0008	0.0071	0.0020	0.0032	0.0009	0.0006
		(5.63)	(2.48)	(4.40)	(2.46)	(1.59)	(3.66)	(2.14)	(4.46)	(1.51)	(1.06)
buy	Wi-Mid	0.0040	0.0003	0.0008	-0.0005	-0.0013	0.0002	0.0006	0.0012	-0.0002	-0.0012
		(2.55)	(0.43)	(1.39)	(-1.08)	(-2.88)	(0.15)	(0.82)	(2.08)	(-0.49)	(-2.80)
sell	Mid-Lo	0.0065	0.0019	0.0023	0.0020	0.0021	0.0069	0.0014	0.0020	0.0012	0.0018
		(4.88)	(2.87)	(4.50)	(4.37)	(4.81)	(4.78)	(2.01)	(3.90)	(2.33)	(3.84)
	DGTW	0.0065	0.0003	0.0016	0.0007	0.0003	0.0057	0.0003	0.0019	0.0006	0.0004
	[Wi-Lo]	(3.99)	(0.44)	(2.99)	(1.72)	(0.91)	(3.33)	(0.36)	(3.47)	(1.42)	(1.10)
6	Wi	0.0176	0.0161	0.0156	0.0136	0.0143	0.0159	0.0155	0.0148	0.0134	0.0142
	Lo	0.0127	0.0118	0.0116	0.0132	0.0140	0.0151	0.0115	0.0116	0.0131	0.0137
	Wi-Lo	0.0049	0.0043	0.0040	0.0004	0.0003	0.0008	0.0040	0.0032	0.0003	0.0005
		(2.35)	(4.24)	(5.01)	(0.67)	(0.63)	(0.41)	(3.96)	(4.17)	(0.52)	(1.00)
buy	Wi-Mid	0.0039	0.0036	0.0029	-0.0001	-0.0004	0.0014	0.0034	0.0021	-0.0002	-0.0002
		(2.51)	(4.38)	(4.55)	(-0.25)	(-0.90)	(0.97)	(4.31)	(3.35)	(-0.32)	(-0.42)
sell	Mid-Lo	0.0010	0.0007	0.0010	0.0005	0.0007	-0.0006	0.0005	0.0011	0.0005	0.0007
		(0.70)	(0.98)	(1.85)	(1.13)	(1.70)	(-0.42)	(0.81)	(2.04)	(1.06)	(1.62)
	DGTW	0.0012	0.0020	0.0024	0.0002	0.0002	-0.0020	0.0021	0.0020	0.0001	0.0003
	[Wi-Lo]	(0.63)	(2.27)	(4.33)	(0.55)	(0.74)	(-1.08)	(2.64)	(3.61)	(0.15)	(0.91)
12	Wi	0.0202	0.0164	0.0143	0.0130	0.0138	0.0194	0.0164	0.0141	0.0128	0.0139
	Lo	0.0117	0.0111	0.0116	0.0132	0.0139	0.0128	0.0110	0.0118	0.0131	0.0138
	Wi-Lo	0.0085	0.0053	0.0026	-0.0002	-0.0001	0.0066	0.0054	0.0023	-0.0002	0.0001
		(3.94)	(5.14)	(3.60)	(-0.43)	(-0.10)	(3.11)	(5.27)	(3.18)	(-0.43)	(0.22)
buy	Wi-Mid	0.0052	0.0038	0.0014	-0.0008	-0.0009	0.0044	0.0035	0.0010	-0.0013	-0.0010
		(3.24)	(4.59)	(2.57)	(-1.83)	(-1.94)	(2.72)	(4.18)	(1.84)	(-2.89)	(-2.10)
sell	Mid-Lo	0.0032	0.0015	0.0012	0.0006	0.0008	0.0022	0.0019	0.0013	0.0011	0.0011
		(2.07)	(2.09)	(2.01)	(1.15)	(1.83)	(1.43)	(2.63)	(2.13)	(2.29)	(2.40)
	DGTW	0.0043	0.0030	0.0018	0.0000	0.0001	0.0023	0.0031	0.0015	-0.0000	0.0002
	[Wi-Lo]	(2.30)	(3.89)	(3.11)	(0.01)	(0.33)	(1.26)	(4.11)	(2.64)	(-0.06)	(0.56)

The Bonferroni-adjusted critical values at the 5% and 1% significance levels are 3.24 and 3.67, respectively.

Table 4: Diagnostics on Industry Momentum Trading Strategies

Summary statistics on the industries which comprise our industry momentum trading strategies are reported below. Results are reported for the **IMS2(1,1)** industry momentum trading strategy, where the winners are the highest three past 1-month return industries, and the losers are the lowest three past 1-month return industries. The table documents the number of times each industry (numbered 1-20) appears in the winners and losers portfolios, the maximum length of time (consecutive months) each industry remained in the winners and losers portfolios, the average rank of each industry (where industries are ranked on their past 1-month returns), the correlation between the rank of each industry at time t and its ranking in the prior period (at time $t-1$), as well as partial autocorrelation coefficients for each industry at 1, 6, 12, and 36 month lags. Partial autocorrelation coefficients are estimated by regressing industry returns on the p most recent lags, for $p = 1, ..., L$, where L is 1, 6, 12, and 36. The results pertain to the July, 1966 to July, 1995 time period (347 months).

	# Months in			Correlation	Partial Autocorrelations			
Industry	Wi(max.)	Lo(max.)	Avg. rank	(rank$_{t,t-1}$)	$\hat{\rho}_{t-1}$	$\hat{\rho}_{t-6}$	$\hat{\rho}_{t-12}$	$\hat{\rho}_{t-36}$
1.	72(2)	22(2)	10.01	-0.0652	0.0658	0.0008	0.0019	-0.0033
2.	80(3)	48(4)	10.32	0.0873	0.0759	0.0002	-0.0000	-0.0013
3.	65(2)	53(2)	10.47	0.0054	0.2187	0.0006	0.0023	-0.0002
4.	59(3)	49(4)	10.21	0.0847	-0.0157	0.0007	-0.0019	0.0008
5.	52(3)	67(4)	10.67	0.0329	0.0046	-0.0002	0.0000	-0.0007
6.	65(3)	70(4)	10.21	0.0153	-0.0477	-0.0002	0.0001	-0.0004
7.	55(2)	68(3)	10.72	-0.0641	0.1411	0.0007	-0.0015	0.0005
8.	53(3)	64(3)	10.56	-0.0109	-0.0088	0.0007	0.0010	-0.0002
9.	58(2)	83(3)	10.96	0.0104	0.1111	0.0008	0.0051	-0.0021
10.	51(4)	75(5)	10.67	0.0700	0.1113	0.0018	0.0016	-0.0014
11.	57(4)	80(4)	10.50	-0.0510	0.0949	0.0004	0.0020	-0.0031
12.	51(3)	81(3)	10.91	0.0355	0.1378	-0.0001	0.0021	-0.0012
13.	46(3)	70(3)	10.73	-0.0182	0.1166	-0.0001	0.0034	0.0000
14.	53(3)	63(2)	10.68	0.0414	0.0779	0.0007	0.0018	-0.0006
15.	50(3)	63(4)	10.65	-0.0070	0.1282	0.0011	0.0007	0.0013
16.	60(4)	51(3)	10.17	0.0661	0.0243	0.0002	0.0002	0.0006
17.	49(3)	57(3)	10.66	0.0170	0.1341	0.0001	-0.0011	-0.0010
18.	52(4)	43(3)	10.25	0.0203	0.1912	0.0001	-0.0003	-0.0012
19.	59(3)	28(3)	10.32	-0.0147	0.1223	0.0007	0.0001	-0.0013
20.	59(5)	11(1)	10.33	0.1280	0.1244	-0.0000	-0.0005	0.0006
Mean	57.3(3.1)	57.3(3.15)	10.5	0.0191	0.0868	-0.0002	-0.0001	-0.0023

Table 5: Impact of Lead-Lag Effects on Industry Momentum Profits

The decomposition of the IMS2(1,1) (skipping a month between the portfolio formation and holding period) momentum strategy profits into various components related to size and dollar trading volume are reported below for the period July, 1963 - July, 1995.

Panel A reports the IMS2(1,1) profits for the largest and smallest 20% of stocks based on market capitalization (size) and dollar trading volume ($Vol). Specifically, the three industries which performed the best and the three which performed the worst at time $t-2$ (i.e., skip a month) are selected, and within each industry, stocks are sorted into quintiles based on their market capitalization ($Vol) at time $t-2$. The average return of the highest size ($Vol) quintiles within each of the three lowest past performing industries is then subtracted from the average return of the highest size ($Vol) quintiles within each of the three highest past performing industries. That is, we restrict securities to only the largest 20% of stocks within *each industry*. The same analysis is repeated for the smallest 20% of stocks within each industry. Stocks are value-weighted so that their weights sum to one.

Panel B decomposes the profits from IMS2(1,1) (skipping a month) into size and $Vol quintiles as described above, however, the weights on the securities are not rebalanced within each quintile to sum to one, so that we can capture the contribution of each size and $Vol category to total profits.

In addition, we report the results using DGTW-adjusted returns, which pertain to the Jan., 1973 to July, 1995 time period.

IMS2(1,1) Profits, Skipping a Month

Panel A: Rebalance to Sum to One

	Size (market capitalization)				$Vol (trading volume)			
	Raw	(t-stat)	DGTW	(t-stat)	Raw	(t-stat)	DGTW	(t-stat)
Largest 20%	0.0077	(4.69)	0.0033	(4.07)	0.0178	(10.37)	0.0092	(8.50)
Smallest 20%	0.0096	(5.12)	0.0033	(3.48)	0.0071	(4.29)	0.0019	(2.41)

Panel B: No Rebalancing

Decomposition of IMS2(1,1) Profits: Value-Weighted industries

	Size (market capitalization)				$Vol (trading volume)			
Quintiles	Profits	%	DGTW	%	Profits	%	DGTW	%
(*low*) 1	0.000103	1.19%	0.000020	0.59%	0.000232	2.77%	0.000076	2.47%
2	0.000284	3.27%	0.000080	2.32%	0.000786	9.37%	0.000164	5.33%
3	0.000696	8.00%	0.000206	5.96%	0.000915	10.92%	0.000328	10.68%
4	0.000156	17.95%	0.000469	13.55%	0.002351	28.04%	0.000616	20.06%
(*high*) 5	0.006046	69.60%	0.002686	77.58%	0.004100	48.90%	0.001886	61.46%
Total:	0.008688		0.003462		0.008384		0.003069	

Table 6: Fama-MacBeth Regressions: individual Stock and Industry Momentum

Fama and MacBeth (1973) cross-sectional regressions are run every month on the universe of securities from Jan., 1973 - July, 1995. Specifically, the cross-section of stock returns, characteristically adjusted for size and BE/ME, at time t are regressed on a constant (not reported) and a host of firm characteristics: market β (estimated using the prior 36 months of returns), size (log of market capitalization at $t-1$), BE/ME, and several individual and industry past return variables. We adjust for size and BE/ME on both the left and right hand side of the regression equation as a better control for these effects.

Panel A reports the time-series average coefficients for regressions that employ various *individual* past return or momentum variables, $ret_{-L:-H}$, which is the return on each stock from $t-L$ to $t-H$. These regressions are performed using (L, H) momentum strategies of (6,1), (6,6), (12,1), and (12,12), where the (6,6) strategy is simply an equal-weighted average of $ret_{-11:-6}, \ldots,$ $ret_{-6:-1}$. The (12,12) return is defined similarly. Each of these regressions are performed in isolation, and in combination with $ret_{-1:-1}$ and $ret_{-36:-13}$ to capture the short-term reversal and long-run reversal effect in individual stock returns.

Panel B reports the time-series average coefficients for regressions that employ various *industry* past return or momentum variables, $ind_{-L:-H}$, which is the return on the industry from $t-L$ to $t-H$ to which each stock belongs. These regressions are performed using (L, H) momentum strategies of (6,1), (6,6), (12,1), and (12,12), where the (6,6) strategy is simply an equal-weighted average of $ind_{-11:-6}, \ldots, ind_{-6:-1}$. The (12,12) return is defined similarly. Each of these regressions are performed in isolation, and in combination with $ind_{-1:-1}$ and $ind_{-36:-13}$ to capture the short-term continuation and long-run reversal effect in industry returns.

Panel C reports the time-series average coefficients for regressions that employ various *individual stock and industry* past return or momentum variables. These regressions are performed using (L, H) momentum strategies of (6,1), (6,6), (12,1), and (12,12). Each of the regressions are performed first with $ret_{-1:-1}$, and $ret_{-36:-13}$, and then with $ind_{-1:-1}$, and $ind_{-36:-13}$ to capture the short-term reversal and long-run reversal effect in individual stock returns and then the short-term continuation and long-run reversal in industry returns, respectively.

Panel D reports the time-series average coefficients for regressions that employ various individual and industry past return or momentum variables that *skip a month* between the variable and the cross-section. Specifically, the individual past return variables become, $ret_{-L-1:-H-1}$, and the industry past return variables are, $ind_{-L-1:-H-1}$. These regressions are performed using (L, H) momentum strategies of (7,2), (6,6*), (13,2), and (12,12*), where the (6,6*) strategy is an equal-weighted average of five past 6-month returns: the returns from t-11 to t-6, . . ., t-7 to t-2. The (12,12*) return is defined similarly. Each of the regressions are performed in combination with $ret_{-1:-1}$, and $ret_{-36:-13}$, and then with $ind_{-1:-1}$, and $ind_{-36:-13}$ to capture the short-term reversal and long-run reversal effect in individual stock returns and the short-term continuation and long-run reversal in industry returns, respectively.

	Cross-Section of Expected Size and BE/ME Adjusted returns								
Strategy	β	ln(Size)	BE/ME	$\mathbf{ret_{-L:-H}}$	$ret_{-1:-1}$	$ret_{-36:-13}$	$\mathbf{ind_{-L:-H}}$	$ind_{-1:-1}$	$ind_{-36:-13}$
(L, H)	**Panel A: Individual Stock Momentum**								
(6,1)	0.0000	0.0001	0.0011	-0.0193					
	(0.02)	(0.46)	(1.62)	(-1.16)					
	-0.0000	0.0001	0.0012	0.0355	-0.0489	-0.0010			
	(-0.07)	(0.87)	(1.64)	(1.90)	(-15.52)	(-3.12)			
(6,6)	-0.0000	0.0000	0.0013	0.0586					
	(-0.08)	(0.06)	(1.84)	(2.36)					
	0.0001	0.0001	0.0014	0.0724	-0.0457	-0.0011			
	(0.13)	(0.49)	(1.87)	(2.91)	(-17.80)	(-3.19)			
(12,1)	-0.0000	0.0000	0.0013	0.0379					
	(-0.12)	(0.24)	(1.79)	(1.29)					
	0.0001	0.0000	0.0014	0.0988	-0.0521	-0.0010			
	(0.19)	(0.19)	(1.92)	(3.11)	(-16.87)	(-3.05)			
(12,12)	-0.0000	0.0000	0.0011	0.0444					
	(-0.05)	(0.04)	(1.72)	(1.57)					
	0.0001	0.0001	0.0011	0.0666	-0.0437	-0.0017			
	(0.18)	(0.55)	(1.77)	(2.17)	(-16.16)	(-4.03)			

Strategy	β	ln(Size)	BE/ME	$\mathbf{ret}_{-L,-H}$	$ret_{-1,-1}$	$ret_{-36,-13}$	$\mathbf{ind}_{-L,-H}$	$ind_{-1,-1}$	$ind_{-36,-13}$
(L,H)	**Panel B: Industry Momentum**								
(6,1)	0.0000	0.0001	0.0010				0.0334		
	(0.11)	(0.35)	(1.55)				(5.48)		
	0.0001	0.0000	0.0010				0.0138	0.1275	-0.0030
	(0.13)	(0.29)	(1.53)				(1.95)	(7.50)	(-1.78)
(6,6)	0.0000	0.0000	0.0010				0.0283		
	(0.11)	(0.20)	(1.55)				(3.61)		
	0.0001	0.0000	0.0009				0.0215	-0.0457	-0.0011
	(0.15)	(0.23)	(1.50)				(2.84)	(9.11)	(-1.24)
(12,1)	0.0000	0.0000	0.0009				0.0234		
	(0.08)	(0.29)	(1.51)				(5.80)		
	0.0000	0.0000	0.0009				0.0148	0.1227	-0.0014
	(0.12)	(0.26)	(1.46)				(3.48)	(7.97)	(-0.91)
(12,12)	0.0000	0.0000	0.0009				0.0092		
	(0.09)	(0.33)	(1.42)				(1.81)		
	0.0001	0.0000	0.0008				0.0113	0.1410	-0.0044
	(0.15)	(0.21)	(1.36)				(2.10)	(9.15)	(-2.43)

(L,H)	**Panel C: Individual Stock and Industry Momentum**								
(6,1)	0.0000	0.0001	0.0013	0.0280	-0.0491	-0.0011	0.0366		
	(0.02)	(0.94)	(1.75)	(1.55)	(-15.61)	(-3.24)	(7.10)		
	0.0000	0.0001	0.0013	0.0302	-0.0511	-0.0010	0.0127	0.1487	-0.0025
	(0.03)	(0.86)	(1.78)	(1.68)	(-16.35)	(-3.16)	(2.08)	(8.86)	(-1.53)
(6,6)	0.0001	0.0001	0.0015	0.0207	-0.0463	-0.0011	0.0237		
	(0.17)	(0.41)	(1.90)	(1.25)	(-18.00)	(-3.33)	(3.67)		
	0.0001	0.0001	0.0014	0.0309	-0.0484	-0.0010	0.0154	0.1542	-0.0015
	(0.23)	(0.44)	(1.92)	(1.49)	(-18.85)	(-3.24)	(2.53)	(10.44)	(-1.02)
(12,1)	0.0001	0.0000	0.0014	0.0873	-0.0522	-0.0010	0.0221		
	(0.23)	(0.27)	(1.94)	(2.84)	(-16.95)	(-3.11)	(6.87)		
	0.0001	0.0000	0.0014	0.0880	-0.0542	-0.0010	0.0116	0.1453	-0.0006
	(0.28)	(0.24)	(1.95)	(2.87)	(-17.59)	(-3.19)	(3.52)	(9.62)	(-0.42)
(12,12)	0.0001	0.0001	0.0011	0.0597	-0.0444	-0.0017	0.0089		
	(0.23)	(0.60)	(1.80)	(2.04)	(-16.50)	(-4.00)	(2.08)		
	0.0001	0.0001	0.0011	0.0571	-0.0468	-0.0016	0.0096	0.1603	-0.0032
	(0.30)	(0.49)	(1.80)	(1.98)	(-17.36)	(-4.06)	(2.13)	(10.55)	(-1.84)

(L,H)	**Panel D: Individual Stock and Industry Momentum (Skip a month*)**								
(7,2)	0.0000	0.0001	0.0014	0.0326	-0.0440	-0.0011	0.0218		
	(0.02)	(0.81)	(1.80)	(1.87)	(-15.58)	(-3.33)	(3.92)		
	0.0000	0.0001	0.0013	0.0321	-0.0461	-0.0010	0.0142	0.1575	-0.0016
	(0.01)	(0.80)	(1.80)	(1.84)	(-16.48)	(-3.18)	(2.55)	(10.22)	(-1.00)
(6,6*)	0.0001	0.0000	0.0015	0.0533	-0.0445	-0.0011	0.0174		
	(0.27)	(0.26)	(1.93)	(1.98)	(-16.31)	(-3.32)	(2.80)		
	0.0001	0.0000	0.0014	0.0542	-0.0467	-0.0010	0.0142	0.1587	-0.0016
	(0.33)	(0.33)	(1.93)	(1.79)	(-17.21)	(-3.25)	(2.41)	(10.74)	(-1.03)
(13,2)	0.0001	0.0000	0.0014	0.0775	-0.0445	-0.0012	0.0156		
	(0.26)	(0.29)	(1.92)	(2.75)	(-16.46)	(-3.71)	(4.72)		
	0.0001	0.0000	0.0014	0.0757	-0.0467	-0.0011	0.0114	0.1566	-0.0010
	(0.35)	(0.30)	(1.93)	(2.70)	(-17.26)	(-3.73)	(3.51)	(10.72)	(-0.70)
(12,12*)	0.0001	0.0001	0.0011	0.0519	-0.0439	-0.0017	0.0073		
	(0.24)	(0.65)	(1.74)	(1.92)	(-15.95)	(-3.88)	(1.69)		
	0.0001	0.0001	0.0010	0.0491	-0.0463	-0.0016	0.0088	0.1628	-0.0033
	(0.30)	(0.55)	(1.73)	(1.83)	(-16.83)	(-3.93)	(1.94)	(10.71)	(-1.88)