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Do Industries Explain Momentum?

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ABSTRACT

This paper documents a strong and prevalent momentum effect in industry components of stock returns which 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.

BOTH INVESTMENT THEORY AND ITS APPLICATION to investment management critically depend on our field's understanding of stock return persistence anomalies. Determining whether these anomalies are rooted in behavior 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 percent abnormal return per dollar long on a self-financing strategy per year) 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 less than one month); it is highly

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profitable 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 returns (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. Specifically, we find strong evidence that persistence in industry return components generates significant profits that may account for much of the profitability of individual stock momentum strategies. We show the following evidence:

- Industry portfolios exhibit significant momentum, even after controlling for size, book-to-market equity (BE/ME), individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences.
- Once returns are adjusted for industry effects, momentum profits from individual equities are significantly weaker and, for the most part, are statistically insignificant.
- Industry momentum strategies are more profitable than individual stock momentum strategies.
- Industry momentum strategies are robust to various specifications and methodologies, and they appear to be profitable even among the largest, most liquid stocks.
- Profitability of industry strategies over intermediate horizons is predominantly driven by the long positions. By contrast, the profitability of individual stock momentum strategies is largely driven by selling past losers, particularly among the less liquid stocks.
- Unlike individual stock momentum, industry momentum is strongest in the short-term (at the one-month horizon) and then, like individual stock momentum, tends to dissipate after 12 months, eventually reversing at long horizons. Thus, the signs of the short-term (less than one month) performances of the industry and individual stock momentum strategies are completely opposite, yet the signs of their intermediate and long-term performances are identical.

The existence of industries as a key source of momentum profits may support the viability of behavioral models that have been offered for the individual stock momentum anomaly. Among these behavioral explanations is Jegadeesh and Titman's (1993) initial conjecture that individual stock momentum is driven by investor underreaction to information. Additionally,

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

several recent behavioral theories rooted in investor cognitive biases have attempted to explain this phenomenon. Among them are Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999). Behaviorally driven momentum profits should at least be constrained by the fact that some rational investors exist who may perceive momentum as an arbitrage opportunity. Rational investors can profit from their irrational counterparts at low risk with positions in large numbers of stocks if the bulk of investors persistently and *irrationally* underreact to information that is sufficiently uncorrelated across firms. There are virtually no limits to this arbitrage if stock returns are generated by a factor model. A self-financing momentum portfolio that is long the high past return stocks and short the 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 rational investors would not exploit such a low-risk near arbitrage.

If behavioral patterns generate the profitability of momentum trading strategies, then these strategies must at least be constrained by factor risk exposure that cannot be eliminated. Such factor risk would limit the size of the positions that rational investors would be willing to take. One contribution of this paper, therefore, is to show that because industry momentum drives much of individual stock momentum, and stocks within an industry tend to be much more highly correlated than stocks across industries, momentum strategies are not very well diversified. Thus, momentum may be a "good deal" but it is far from an arbitrage.

Industry momentum profits may also be indicative of an important role for industries in understanding financial markets. Previous literature has shown relatively little impact of industries on asset prices, either domestically or in international markets.[2] This stands in marked contrast to the corporate finance literature, which recognizes the importance of industries in explaining hot and cold IPO and SEO markets and merger and acquisition activity, as well as other investment and financial policy decisions. Most of the asset pricing studies, however, examine the unconditional return distribution of industry portfolios. We find an extremely strong industry influence when we condition returns on the information in past prices. The importance of industries in conditional asset pricing may be consistent with recent behavioral and rational theories for momentum. In the last section of the paper, we offer some conjectures about why the momentum phenomenon is linked to industry.

[2] See, for instance, Fama and French (1997) and evidence in this paper, as well as Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998), for lack of an industry influence in international markets. The exception to this is Roll (1992).

The paper is organized as follows. Section I briefly describes the data and formation of our industries. Section II motivates the paper by presenting a simple return generating process, and discusses various sources of momentum profits. Section III isolates these potential sources of momentum profits and finds a large and significant industry influence that seems to account for much of the momentum anomaly. Section IV 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 V then evaluates the interaction between industry momentum and individual stock momentum for explaining the cross section of expected stock returns. Section VI concludes the paper by summarizing our findings and offering several economic stories for the existence and importance of industry momentum.

I. Data Description and Industry Returns

Using the CRSP and COMPUSTAT data files, 20 value-weighted industry portfolios are formed for every month from July 1963 to July 1995. Two-digit Standard Industrial Classification (SIC) codes[3] 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 (1994b) and Jorion (1991). Table I 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 at any time in any industry except Railroads is more than 25. Therefore, virtually all portfolios are well diversified in that they have negligible firm-specific risk.

Table I reports the average monthly raw excess returns of the 20 industries. An F-test of whether these mean returns differ across industries is not rejected, suggesting there is little cross-sectional variation in our industry sample means. We adjust industry returns for size (market capitalization) 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.[4] Table I 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

[3] 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.

[4] See, for example, Banz (1981), Rosenberg, Reid, and Lanstein, (1985), Fama and French (1992, 1993, 1996), and Daniel and Titman (1997).

excess of these size and BE/ME benchmarks represents the industry abnormal return.[5] As Table I shows, there is little evidence that unconditional abnormal industry returns exist per se.[6]

II. 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.

A. 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 security 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, and, being less pervasive than the factors mimicked by the R's, not bearing unconditional risk premia), θ_{jm} are stock j's sensitivities to the z components, and $\tilde{\epsilon}_{jt}$ is stock j's firm-specific return component at date t. The mean zero firm-specific components 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

[5] 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 characteristics-matched portfolio adjustment method as opposed to a regression on prespecified 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.

[6] Indeed, the most significant of the 20 univariate tests that industry abnormal returns significantly differ from zero fails to exceed the 5 percent significance bound derived from the Bonferroni inequality, which accounts for the inspection of multiple industries, and we fail to reject an F-test that the abnormal returns differ across industries.

Table I

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 is reported, along with the minimum number of stocks appearing in each portfolio at any point in time (reported in parentheses). Also reported are the average percentage of total market capitalization, the average return in excess of the three-month Treasury bill rate, the return standard deviation, and the average abnormal return in excess of size and BE/ME matched benchmarks (t-statistics are in parentheses) of each industry over the sample period, 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-statistic for whether the mean returns and abnormal returns are significantly different from zero, as well as an F-statistic that the returns are equal across industries (with p-values in parentheses). The size- and BE/ME-adjusted returns correspond to the January 1973 to July 1995 time period. The Bonferroni-adjusted critical values at the 5 percent and 1 percent levels are 3.10 and 3.34, respectively.

Industry	SIC Codes	Avg. No. of 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	22-23	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	38-39	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.	41-47	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	50-52, 54-59	377.06 (143)	3.34%	0.0055	0.0021	(1.41)
19. Financial	60-69	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)
F-statistic (all = 0)				2.920	1.686	
(p-value)				(0.000)	(0.034)	
F-statistic (all the same)				0.825	1.38	
(p-value)				(0.677)	(0.136)	

one another.[7] Empirical research in finance has suggested that these factor portfolios capture the cross section of expected returns within the feasible set of *semipassive* strategies (in a sense to be defined shortly). That is, the unconditional expected return of stock j is

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

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

Equivalently, we are stating that mean variance efficient semipassive 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 *semipassive* strategies in that they adjust portfolio weights on assets as they 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 semipassive strategy is rather low. For expositional simplicity, therefore, we pretend that the changes in sensitivity to these semipassive portfolios (i.e., book-to-market, size, etc.) and factor risk premia 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 onto the optimal semipassive portfolios (such as the Fama–French factor portfolios). In principle, of course, 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. However, for expositional simplicity, we currently interpret the z's as only being industry-related. As documented in Table I 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.[8] By contrast, the firm-specific return components should carry no risk premia 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 semipassive strategies that are generated by analyzing the sensitivities of stocks to size, book-to-market, and market factors alone, 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, the expected returns of assets conditional on the information at time t, ϕ_t, are represented by the following equation:

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

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

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

$$E[\tilde{R}_{kt}\tilde{R}_{lt-1}] = 0, \quad \forall k \neq l;$$

$$E[\tilde{R}_{kt}\tilde{\delta}_{mt-1}] = 0, \quad \forall k,m;$$

$$E[\tilde{R}_{kt}\tilde{\epsilon}_{jt-1}] = 0, \quad \forall k,j;$$

$$E[\tilde{\delta}_{mt}\tilde{\delta}_{nt-1}] = 0, \quad \forall m \neq n;$$

$$E[\tilde{\delta}_{mt}\tilde{\epsilon}_{jt-1}] = 0, \quad \forall m,j;$$

$$E[\tilde{\epsilon}_{jt}\tilde{\epsilon}_{it-1}] = 0, \quad \forall j \neq i;$$

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.

B. 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 is easy to interpret. It is also possible to focus on self-financing portfolios with weights that are linear functions of measured momentum (e.g., past returns). One such portfolio, which has returns that are highly correlated with the decile portfolios used in past research, has expected returns that are expressed as

$$E[(\tilde{r}_{jt} - \bar{r}_t)(\tilde{r}_{jt-1} - \bar{r}_{t-1})], \tag{4}$$

where $\bar{r}_t$ is the cross-sectional or equal-weighted average return of stocks at time t (in this section the overbar represents a variable's cross-sectional average). Expression (4) represents the expected payoff to a self-financing momentum investment strategy where $(\tilde{r}_{jt-1} - \bar{r}_{t-1})$ is the amount invested in stock j at time t, funded by shorting the same amount in the equal-weighted portfolio. Momentum in stock returns implies that this expression is positive. There are notational advantages to decomposing the returns to the linear portfolio expressed in equation (4), as opposed to analytically decomposing the returns of the equal-weighted decile-based portfolios. Hence, we employ the linear approach for our subsequent analytical decomposition.

We take liberties in interpreting the average 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.[9]

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

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

Averaging over all N stocks, momentum trading profits equal

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

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.

Equation (6) suggests that there are four sources of momentum trading profits from individual stocks. The first is σ_μ^2, the cross-sectional variation in unconditional mean 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 (semipassive) portfolios. Thus, if profits from a book-to-market, size, or market beta-based strategy are positively serially correlated, this second term would be positive. The third term, $\sum_{m=1}^{M} \sigma_{\theta_m}^2 \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1})$, is the con-

[9] 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).

tribution to momentum of serial correlation in industry return components. The last term represents serial covariation in firm-specific components, $\mathrm{Cov}(\tilde{\epsilon}_{jt}, \tilde{\epsilon}_{jt-1})$.

Conrad and Kaul (1998) claim that the first term largely contributes to momentum profits. Jegadeesh and Titman's (1993) underreaction story suggests that serial correlation in components of returns that are not related to factors is primarily responsible for momentum trading profits. Jegadeesh and Titman (1993) thus assert that either the δ's or the ϵ's, or both, generate momentum.

Evidence in the next section demonstrates that, at least for six-month momentum, most of the trading profits arise from the third term, $\sum_{m=1}^{M} \sigma_{\theta_m}^2 \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1})$, implying that the cross section of expected returns, conditional on last period's returns, can be reasonably summarized as follows:

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

III. Isolating Sources of Momentum Trading Profits

A. Momentum Investment Strategies

To analyze the components in equation (6), we form winners − 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. We then hold 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 do the same.

In our analysis, the six-month, six-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 percent of stocks *every month* from t to $t + 5$ minus the value-weighted return of the lowest 30 percent of stocks every month from t to $t + 5$. This procedure is then repeated at time $t + 1$, and so forth.

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 and 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 1991 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 this January 1992 return to bid-ask bounce (in the case of individual stock momentum) or a lead-lag effect (in the case of industry momentum).[10]

A.1. Raw Profits

We employ 30 percent breakpoints to determine winners and losers, and we value weight the returns of stocks with momentum rankings in the top 30 percent and bottom 30 percent to compute the returns of the winning and losing portfolios. The individual stock momentum strategy (shown in Table II, Panel A) generates a return (per dollar long) of about six percent per year, which is lower but statistically more significant than the momentum-based portfolio return reported in Jegadeesh and Titman (1993).[11] In the following subsections, we decompose this six percent zero-cost return into various components in order to identify the primary source of this profit.

A.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 six percent per year momentum profit. The equal-weighted index 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., $\bar{\theta}_m$ is very small for all m). Thus, the serial covariance of the equal-weighted portfolio of all stocks is approximately,

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

where t is a six-month period. This allows us to isolate one of the components of momentum profits. Using *raw, monthly–rebalanced*, equal weighted portfolio returns, we find (as did Jegadeesh and Titman (1993)), that the covariance of consecutive nonoverlapping six-month returns on the equal-

[10] Lo and MacKinlay (1990) document 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.

[11] Jegadeesh and Titman (1993) document an annual 12 percent return per dollar long for their six-month, six-month strategy. Their return is larger than ours because they equal-weight the stocks within their winner and loser portfolios and they use 10 percent breakpoints. Equal weighting the stocks and employing 10 percent breakpoints increases the average return and volatility of the strategy, but does not change our conclusions. Equal weighting of stocks within the 30 percent categories (rebalancing monthly) produces profits of about 9.3 percent per year. We value weight within the winner and loser portfolios because our risk adjustment method (used later) is based on matching stocks with value-weighted benchmarks. Furthermore, 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.

Table II

Momentum Profits for Individual Equities, Industries, and Random Industries

Panel A reports average monthly profits of winners minus losers, Wi − Lo (the highest 30 percent minus the lowest 30 percent), momentum portfolios of individual equities for July 1963 through July 1995 (i.e., $T = 383$). Portfolios are formed based on $L = 6$-month lagged returns and held for $H = 6$ months. The L-month lagged returns are always raw returns, to be used for portfolio formation. Results are reported for holding period raw, DGTW, size- and BE/ME-adjusted ($\tilde{r}_{jt}^{sb}$), raw minus industry, size- and BE/ME-adjusted minus industry ($\tilde{r}_{jt}^{sb,I}$), and size- and BE/ME-adjusted minus "random" industry returns ($\tilde{r}_{jt}^{sb,\spadesuit}$). Portfolios using size- and BE/ME-adjusted or DGTW-adjusted returns pertain to the January 1973 through July 1995 time period.

Panel B reports average monthly profits of momentum strategies of industries, where industries are sorted on their past six-month raw returns and a zero investment strategy is formed that is long the three highest past return industries and short the three lowest, holding the positions constant for six months, and recomputing the strategy monthly. Raw and DGTW-adjusted profits are reported for the industry momentum strategies. Momentum profits are reported for the random industries as well, where random industries are sorted on their past six-month returns and positions are held for six months (i.e., the (6,6) strategy). The random industries are generated by replacing each stock return with an equal-weighted average of the stocks ranked above and below it based on their past six-month returns.

Panel C reports the raw profits of the industry-neutral, excess-industry, and high-industry losers minus low-industry winners portfolios. For the industry-neutral portfolio, stocks are sorted on their past six-month returns *within* each industry; the top 30 percent of stocks within each industry are value weighted to form the winners portfolio and the bottom 30 percent of stocks within each industry are value weighted to form the losers portfolio. The zero investment return per dollar of the winners minus losers portfolio is then computed over the next six months and averaged over time. Likewise, the excess industry portfolio is formed by first ranking stocks on their past six-month returns in excess of their industry average past six-month return, and a winners minus losers strategy is formed using 30 percent breakpoints. Finally, a strategy is formed that is long the 30 percent worst past six-month return stocks from the three best past six-month performing industries, and short the best 30 percent past six-month return stocks from the three worst performing industries. The profits from this high industry losers minus low industry winners strategy are then computed over the next six months.

Panel A: Individual Stock Momentum

(L,H)		Raw $\tilde{r}_{jt}$		DGTW $\tilde{r}^*_{jt}$		Size and BE/ME $\tilde{r}^{sb}_{jt}$		Raw − Industry $\tilde{r}_{jt} - \tilde{R}_{It}$		Size and BE/ME − Industry $\tilde{r}^{sb,I}_{jt}$		Size and BE/ME − Random Industry $\tilde{r}^{sb,\spadesuit}_{jt}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi − Lo	0.0043	(4.65**)	0.0009	(1.56)	0.0029	(3.34**)	0.0013	(2.04*)	0.0008	(0.91)	0.0027	(2.77**)

Panel B: Industry and Random Industry Momentum

(L,H)		Raw Industry $\tilde{R}_{It}$		DGTW Industry $\tilde{R}^*_{It}$		Raw Random Industry $\tilde{R}^{\spadesuit}_{It}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi − Lo	0.0043	(4.24**)	0.0020	(2.27*)	−0.0005	(−1.09)

Panel C: Individual Stocks, Raw Returns

(L,H)		Industry Neutral $\tilde{r}_{jt}$		Excess Industry $\tilde{r}_{jt}$		High Ind. Losers − Low Ind. Winners $\tilde{r}_{jt}$	
		Mean	(t-stat)	Mean	(t-stat)	Mean	(t-stat)
(6,6)	Wi − Lo	0.0011	(1.01)	−0.0007	(−0.83)	0.0030	(2.66**)

*,** Significant at the 5 and 1 percent levels, respectively.

weighted index is insignificantly different from zero, $\mathrm{Cov}(\bar{r}_t, \bar{r}_{t-1}) = -0.0001$. Furthermore, since the risk premium of this portfolio is historically high (which implies that some of the $\bar{\beta}_k$'s of this portfolio must be large), serial covariation in at least some of the unconditionally efficient portfolios (e.g., the $\tilde{R}$'s) is not contributing to momentum profits. Additionally, the serial covariance for consecutive six-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 six-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, we find that investing in the factor-mimicking portfolio that had the highest prior return and shorting the factor portfolio that had the lowest produces negative profits of -0.0005 (t-statistic $= -0.42$). Thus, persistence in the returns represented by the R_k's are not driving momentum-trading profits.

B. Industry Momentum Profits

Sorting industry portfolios (which value weight stocks within the industry) based on their past six-month returns, and investing equally in the top three industries while shorting equally the bottom three industries (holding this position for six months) produces average monthly profits (shown in Table II, Panel B) of 0.43 percent—identical in magnitude to those obtained from the momentum strategy for individual equities. We 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.

Aggregating stocks into industry portfolios largely eliminates the firm-specific components of returns ($\tilde{\epsilon}$) because industries contain approximately 230 stocks on average. Furthermore, the existence of industry momentum profits of the same magnitude as individual stock momentum profits suggests that dispersion in unconditional mean returns does not drive momentum profits. The cross-sectional variance of ex post mean industry monthly returns, $\sigma^2_{\mu_I}$, 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 I) 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.[12]

[12] 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 0.0081 per month or 10.2 percent per year (t-statistic = 7.71), which is about 90 basis points *higher* than the equal-weighted momentum strategy for individual equities described in footnote 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,

$$\frac{1}{20}\sum_{I=1}^{20} E[(\tilde{R}_{It} - \bar{r}_t)(\tilde{R}_{It-1} - \bar{r}_{t-1})] = \sigma_{\mu_I}^2 + \sum_{k=1}^{K} \sigma_{\beta_{Ik}}^2 \mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) + \sum_{m=1}^{M} \sigma_{\theta_{Im}}^2 \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1}), \tag{9}$$

where $\tilde{R}_{It}$ is the return of industry portfolio I at time t,[13] and $\bar{r}_t$ is the equal-weighted average return across the industry portfolios.[14] Moreover, as previously noted, $\sigma_{\mu_I}^2$ is small for our sample of industries and (at least for the Fama–French factor portfolios) $\mathrm{Cov}(\tilde{R}_{kt}, \tilde{R}_{kt-1}) \approx 0$. Thus, the existence of industry momentum profits, the absence of factor serial correlation, and negligible cross-sectional industry mean return dispersion implies

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

B.1 Size and BE/ME-Adjusted Profits

Although we find little evidence of significant dispersion in mean returns across industries, our conclusions are based on ex post sample means. Ideally we would like estimates of the ex ante mean return dispersion. Therefore, we need to forecast mean returns using known variables. Relying on a host of previous literature, we use the size and BE/ME of a firm to accomplish this. Not only have these two variables been shown to predict average returns, but other studies (including Lakonishok, Shleifer, and Vishny (1994), Asness (1995), and Fama and French (1996)) have shown that momentum is correlated with size and BE/ME. Thus, we adjust returns for these two effects in order to isolate the momentum effect in addition to controlling for ex ante mean returns.

Our control is the Daniel and Titman (1997) size and BE/ME characteristic-adjusted return, described in Section II, which we denote as

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

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

[14] The equal-weighted average return across the industry portfolios is highly correlated with the equal-weighted index of all securities (correlation = 0.95). Hence, we denote both by $\bar{r}_t$, and treat them as essentially the same return.

where $\tilde{r}_{jt}$ is the return on security j, and $\tilde{R}_t^{SB_{j,t-1}}$ is the return on the size and BE/ME-matched portfolio.[15] Adjusting holding period returns for size and BE/ME does not significantly reduce momentum profitability, as Table II shows. The six-month, six-month momentum strategy holding period returns (adjusted for size and BE/ME) remain strong, producing abnormal mean profits of 0.29 percent per month (with a highly significant t-statistic of 3.34), which is about two-thirds the size of the raw profits and does not significantly differ from the raw return momentum number (the difference is about 13 basis points per month with a t-statistic of 1.40).[16]

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 six months of historical returns.

B.2. DGTW Adjusted Profits

We have shown that size and BE/ME do 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 past returns or momentum.[17] The first row of Table II, 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 that

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

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

[16] Prior to 1980, when the size effect was strong, there was a marginally significant (t-statistic = 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 six basis points (t-statistic = 0.67).

[17] DGTW assign stocks to one of five categories based on the prior period’s market capitalization, then within each of these groups they 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., $\tilde{r}_{jt} - \tilde{R}_t^{b_{j,t-1}}$, where the latter is the month t return of the matched characteristic-based portfolio for stock j). The DGTW return, as well as the size- and BE/ME-adjusted returns, pertain to the January 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 are detected when examining the raw return profits over the January 1973 to July 1995 time period.

where $\tilde{r}^*_{jt}$ is the DGTW-adjusted return and $\bar{r}^*_t \approx 0$ ($\bar{r}^*_t = 0.0003$ with a t-statistic of 0.31). Since the equal-weighted index 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. Thus, 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 percent 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 percent of the individual stock strategy's variation over the sample period, and more than 38 percent of the industry momentum strategy's variation.

However, if industry momentum exists that is unique from individual stock momentum (or drives individual stock momentum), then employing these past return benchmarks on industry returns should not eliminate industry momentum profits entirely. That is,

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

where $\tilde{R}^*_{It}$ is the industry return composed of a value-weighted sum of $\tilde{r}^*_{jt}$'s for all $j \in I$, $\sigma^2_{\mu^*_I}$ is the cross-sectional variation in mean returns of our value-weighted industry portfolios, 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 $\sum_{m=1}^{M} \sigma^2_{\theta^*_{Im}} \mathrm{Cov}(\tilde{\delta}_{mt}, \tilde{\delta}_{mt-1})$ remains as the only possible source of profits. Thus, if industry momentum still exists, this component must be significantly positive.

Aggregating the individual DGTW-adjusted stock returns, $\tilde{r}^*_{jt}$'s, into industry portfolios, we find that industry momentum profits are still significant, producing average monthly profits of 0.20 percent (t-statistic = 2.27), as shown in Table II, Panel B. 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 percent does not significantly differ from the DGTW-adjusted profit of 0.20 percent, indicating the reduction in mean returns may be a chance event. Also, because 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 momentum profit is slightly lower than the raw profit.

Moreover, since DGTW-adjusted industry average returns exhibit negligible variation across industries and since industry portfolios 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

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

indicating that serial covariation in industry components is generating significant profits.

Finally, 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 also unlikely that misspecification of the asset pricing model is driving the industry momentum profitability we are reporting.

B.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. 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 six-month, six-month individual stock momentum profits are reported in Table II, Panel A. As the table shows, the profits decline to a marginally significant (t-statistic = 2.04) 13 basis points per month. The 13 basis points is largely due to the size effect from the first half of our sample. 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 produce negligible profits. Specifically, these size-, BE/ME-, and industry-adjusted returns are defined as

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

where $\tilde{R}_{It}^{sb}$ is the size- and BE/ME-adjusted return on industry I, to which stock j belongs at time t, and $\tilde{r}_{jt}^{sb}$ is as previously defined in equation (11). The individual stock momentum strategy generates size-, BE/ME-, and industry-adjusted returns of

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

Having previously shown that the first term on the right-hand side is zero, we show that 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 II, Panel A, reports the results for the six-month, six-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.

B.4. "Random" Industry Portfolios

To punctuate this point we also analyze "random" industry portfolios, replacing every true stock in industry I with another stock that had virtually the same past six-month return.[18] "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 component $\tilde{\delta}$. There-

[18] Ranking all stocks in ascending order based on their prior six-month returns, we form "random" industry portfolios by replacing each stock in an industry with a stock that has the next highest momentum characteristic (six-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 six-month prior returns, stock j belonging to industry I is replaced with stock $j + 1$'s return, for all $j = 1,\ldots,N$. 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 $(\tilde{r}_{j+1,t} + \tilde{r}_{j-1,t})/2$). To avoid endpoint problems, we replace stock N with stock $N - 1$ and stock 1 with stock 2.

fore, 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 than to have been selected from the same industry. Thus, because the stocks in "random" industries have approximately the same past return vector as the vector of stock returns in the true industry, they will exhibit significant momentum if other components, besides industry, drive momentum. As Table II, Panel B, demonstrates, however, momentum profits are nonexistent for the random industries (denoted as $\tilde{R}_{It}^{\spadesuit}$), and momentum profits for individual stocks are virtually unaltered by the random industry adjustment (Table II, Panel A), consistent with the *true* industry being the important component behind momentum profits.

B.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 six-month returns, and the value-weighted average return of the top 30 percent of stocks minus the bottom 30 percent of stocks *within the industry* is computed at time t and held for six months. We refer to this portfolio as an "industry-neutral" portfolio because low past return stocks are subtracted from high past return stocks within the same industry. As Table II 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 nonexistent.

For the second portfolio, stocks are ranked globally based on their past six-month return in excess of their industry average over the same time period. The equal-weighted average return of the top 30 percent of stocks minus the bottom 30 percent based on the excess return ranking is computed at time t (and held for six months). We refer to the second portfolio as an "excess-industry" portfolio because we select our winning and losing stocks based on their past returns in excess of the industry benchmark. As Table II shows, the excess industry portfolio does not exhibit significant profits (mean = -0.0007, t-statistic = -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 that performed the best over the last six months, we rank stocks within each of these industries based on their prior six-month returns and form a value-weighted portfolio of the *bottom* 30 percent of stocks within each of these three high past performing industries. Likewise, we form a value-weighted portfolio of the *top* 30 percent of past six-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 II shows, this portfolio produces positive and significant profits of 0.30 percent per month, indicating the importance of industries in generating momentum profits.

IV. Robustness of Industry Momentum Strategies

Previously, we employed 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 exclusively on the buying and selling of stocks and industry portfolios based on their past six-month returns for portfolios that were held for six months. This section analyzes whether this strong industry momentum effect exists at other horizons as well.

Ranking the 20 industries based on their L-month lagged returns, we form portfolios of the highest and lowest past performing industries, hold them for H months, and rebalance monthly. Again, our strategy is long the highest three past performing industries and short the lowest three.[19] We refer to the L-month lagged, H-month holding period strategy as $\mathrm{IM}(L,H)$. A breakdown of the $\mathrm{IM}(L,H)$ strategies for various ranking periods and horizons is provided in Table III, which reports the L = 1-, 6-, 12-month and H = 1-, 6-, 12-, 24-, 36-month strategies.

The results in Table III are consistent with the findings of Jegadeesh and Titman (1993) for individual stock returns, where momentum profits are strong over intermediate holding periods (3 to 12 months), but diminish beyond a year. The negative returns from the L = 24-month, H = 36-month strategy are consistent with the findings of DeBondt and Thaler (1985), who document long-run (three- to five-year) negative autocorrelation in returns for individual stocks. However, the economic magnitude of these long-run reversals is small.[20] Finally, in contrast to individual stock momentum, industry momentum appears to be most profitable in the very short term (one month). In fact, as Jegadeesh (1990) documents, individual stock momentum strategies produce large *negative* profits at one-month horizons. This discrepancy between industry and individual stock momentum in the very short term is an issue we address later in the paper.

A. Trading Frictions and Lead-Lag Effects

Industry momentum strategies that rank on six months and hold for six months, which we focused on earlier, require turnover of approximately 200 percent per year. Breakeven transaction costs are therefore approxi-

[19] Other industry momentum trading strategies were employed using more industries in the buy and sell portions of the strategy. The results remained largely the same and are excluded for brevity.

[20] When fewer industries are included in the long and short positions, we find stronger long-run reversals, consistent with DeBondt and Thaler (1985), who find that long-term reversals are concentrated in the most extreme securities.

Table III
Industry Momentum Trading Profits

Average monthly profits of the industry momentum trading strategies over the July 1963 through 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 IM(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 January 1973 to July 1995 time period. The Bonferroni-adjusted critical values at the 5 percent and 1 percent significance levels are 3.24 and 3.67, respectively.

		Panel A: No Gap					Panel B: Month Skipped				
L	*H* =	1	6	12	24	36	1	6	12	24	36
1	Wi	0.0193	0.0140	0.0143	0.0137	0.0138	0.0138	0.0135	0.0142	0.0134	0.0137
	Lo	0.0088	0.0118	0.0112	0.0122	0.0130	0.0137	0.0116	0.0110	0.0125	0.0131
	Wi − Lo	0.0105	0.0022	0.0032	0.0015	0.0008	0.0001	0.0020	0.0032	0.0009	0.0006
		(5.63)	(2.48)	(4.40)	(2.46)	(1.59)	(0.03)	(2.14)	(4.46)	(1.51)	(1.06)
buy	Wi − Mid	0.0040	0.0003	0.0008	−0.0005	−0.0013	−0.0019	0.0006	0.0012	−0.0002	−0.0012
		(2.55)	(0.43)	(1.39)	(−1.08)	(−2.88)	(−1.32)	(0.82)	(2.08)	(−0.49)	(−2.80)
sell	Mid − Lo	0.0065	0.0019	0.0023	0.0020	0.0021	−0.0020	0.0014	0.0020	0.0012	0.0018
		(4.88)	(2.87)	(4.50)	(4.37)	(4.81)	(−1.39)	(2.01)	(3.90)	(2.33)	(3.84)
	DGTW	0.0065	0.0003	0.0016	0.0007	0.0003	−0.0005	0.0003	0.0019	0.0006	0.0004
	[Wi − Lo]	(3.99)	(0.44)	(2.99)	(1.72)	(0.91)	(−0.33)	(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)

mately 75 basis points per dollar of one-way long or short transactions. Consistent with the results on individual stock momentum, Table III 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 percent 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 break-even 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, as not all stocks are easily borrowed for a short sale and short sales proceeds and margins often earn less than a market rate of return. Table III reports the profits of the winners minus the losers (Wi − Lo), as well as the winners minus the middle three industries (Wi − Mid) and the middle minus the losers (Mid − Lo), to gauge whether industry momentum profits are largely driven on the buy side (long positions) or sell side (short positions). 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 (see, e.g., Hong, Lim, and Stein (1999)), 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 percent. The middle three industries exceed the bottom three momentum-ranked industries by an average of 0.07 percent per month, as shown in Table III. Thus, industry momentum strategies appear to profit mostly on the buy side, making short sales constraints less of an impediment to their profitability than is the case for individual stock momentum strategies.

Furthermore, prior research, as found for example in Lo and MacKinlay (1990) and Jegadeesh and Titman (1995a, 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 days and weeks earlier. This effect is strongest at shorter horizons and may be due to delayed price reactions of small firms to common factors, as Boudoukh, Richardson, and Whitelaw (1994a) suggest. If these "lead-lag" effects are driving industry momentum, then this will impact our designated strategies and may severely limit the potential profitability of such strategies. Therefore, it is important to examine the impact of lead-lag effects on our industry momentum portfolios.

If lead-lag effects are confounding our results, they will show up most strongly in the month closest to portfolio formation. 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 because our six-month, six-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 III, Panel B. As the table shows, the data seem to support our assertion. Lagging the ranking period by one month, and implementing the analogous momentum strategy, the average monthly return is 0.40 percent (shown in Table III, Panel B), which negligibly differs from the 0.43 percent per month average return for industry momentum reported in Table III, Panel A (which does not skip a month).

Some researchers, notably Grundy and Martin (1999), have argued that industry momentum may be due to lead-lag effects that are not due to firm size. This is almost tautological. If, indeed, individual stock momentum does not exist intra-industry, as Table II, 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 illiquidity, then this may severely limit our ability to profit from these strategies. We address these issues shortly and demonstrate that these effects do not significantly influence our results.

Looking across the rows of Table III 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 to arbitrage away momentum on the downside. This asymmetry may also be consistent with some of the conjectures in Hong et al. (1999) pertaining to analyst coverage and analysts withholding bad information. We come back to these issues in the last section of the paper.

Finally, Table III also reports the profits for various L,H industry momentum strategies adjusting returns for size, BE/ME, and *individual stock momentum* effects via DGTW.[21] As the table shows, the industry momentum

[21] We regress these DGTW-adjusted profits on the Carhart (1997) factors (Fama and French factors plus a winners minus losers individual stock momentum "factor") in order to account for any potential remaining effects of size, BE/ME, or individual stock momentum. The results are nearly identical.

strategies remain substantially profitable, further indicating that industry momentum is stronger than and seems to dominate individual stock momentum.

B. The One-Month, One-Month Industry Momentum Trading Strategy

As Table III indicates, the strongest industry momentum strategy is the one-month lagged, one-month holding period strategy, both raw and adjusting for risk with the DGTW method. In contrast to the six-month, six-month industry momentum strategy, where the long positions generate most of the profit, the profitability of the one-month, one-month industry momentum strategy appears to be equally driven by the long and the short sides of the position. Also in contrast to the six-month, six-month strategy, the one-month, one-month strategy's turnover ratio would seem to preclude profits after transaction costs, despite its significantly 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 one-month, one-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 six-month, six-month strategy is closely linked to the profitability of an industry six-month, six-month strategy, the one-month serial correlation for individual stocks appears to be of the opposite sign to the one-month serial correlation for industries. One possible explanation for the discrepancy between short-term (one-month) reversals for individual stocks and short-term continuations 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.

Table IV reports summary statistics on the IM(1,1) trading strategy and documents that it is a broad-based phenomenon. As the table shows, the most any industry appears in the winners' category is 80 months (Food & Beverage) out of a possible 347, or 23 percent of the time. Likewise, the most any industry appears in the losers' category is 83 months (Fabricated Metals). The maximum number of *consecutive* months an industry appears in either the winners or the losers portfolio is five. Thus, neither the winners nor the losers portfolio seems to be dominated by a particular industry. In fact, the average rank of each industry only ranges from 10.01 to 10.96, further indicating that certain industries are not more likely to be classified as winners or losers than others.

Furthermore, there appears to be little relation between the sample mean returns of the industries and the frequency with which they appear in the winners' and losers' categories. For example, Table I indicates that the five highest sample mean return industries are Food and Beverage, Petroleum, Manufacturing, Railroads, and Retail. However, only two, Food and Beverage and Petroleum, appear in the winners portfolio more often than the

Table IV

Diagnostics on Industry Momentum Trading Strategies

Summary statistics on the industries that comprise our industry momentum trading strategies are reported below. Results are reported for the IM(1,1) industry momentum trading strategy, where the winners are the highest three past one-month return industries, and the losers are the lowest three past one-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 one-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 $p = 1,\ldots,L$, where L is 1, 6, 12, and 36. The results pertain to the July 1966 to July 1995 time period (347 months).

	No. of Months in			Correlation	Partial Autocorrelations			
Industry	Wi (max.)	Lo (max.)	Avg. Rank	($\text{rank}_{t,t-1}$)	$\hat{\rho}_{t-1}$	$\hat{\rho}_{t-6}$	$\hat{\rho}_{t-12}$	$\hat{\rho}_{t-36}$
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

average industry, and only two, Food and Beverage and Retail, appear in the winners portfolio more often than they do 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 IV, further indicate that the winners and losers are not dominated by the same industries and that cross-sectional dispersion in mean returns (due to poor risk adjustment), which should induce high correlation between rankings from one period to another, is not driving momentum profits. Table IV 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.

C. The Lead-Lag Effect and One-Month, One-Month Industry Momentum

In contrast to the longer term industry momentum analyzed earlier, the remarkably strong one-month industry momentum effect may be most affected by a potential lead-lag effect. In the preceding subsection, we find that skipping a month eliminates the profitability of the one-month, one-month industry momentum strategy entirely. One explanation for this reduction in profitability is that skipping a month mitigates market microstructure effects that induce a lead-lag relation among stocks. In this subsection, we present evidence that this is not the case. The reduction in profitability arising from skipping a month is simply due to the autocorrelation effect being weaker from a more distant ranking period.

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 that performed the best and the three that performed the worst over the previous month. Then, within each industry, we sort stocks into quintiles based on their market capitalization at the end of month $t - 1$. 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 percent 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 one-month, one-month industry momentum profits, then restricting the industries to contain only the largest stocks should produce significantly reduced profits.

As Panel A of Table V shows, the one-month, one-month momentum profits for the largest 20 percent of stocks in each industry are 0.99 percent per month, and they are of the same order of magnitude as the IM(1,1) profits reported previously, which employ all stocks in the industry. This suggests that lead-lag effects due to firm size are not materially affecting the reported profits.

Table V

Impact of Lead-Lag Effects on Industry Momentum Profits

The decomposition of the IM(1,1) momentum strategy profits into various components related to size and dollar trading volume are reported for the period July 1963–July 1995. Panel A reports the IM(1,1) profits for the largest and smallest 20 percent of stocks based on market capitalization (size) and dollar trading volume ($Vol). Specifically, the three industries that performed the best and the three that performed the worst at time $t-1$ are selected, and, within each industry, stocks are sorted into quintiles based on their market capitalization ($Vol) at time $t-1$. 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 the largest 20 percent of stocks within *each industry*. The same analysis is repeated for the smallest 20 percent of stocks within each industry. Stocks are value weighted so that their weights sum to one. Panel B decomposes the profits from IM(1,1) into size and $Vol quintiles as described above, but 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. We report the results using both raw and DGTW-adjusted returns, which pertain to the January 1973 to July 1995 time period.

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%	0.0099	(5.89)	0.0043	(3.54)	0.0156	(9.27)	0.0068	(5.54)
Smallest 20%	0.0178	(9.71)	0.0057	(4.51)	0.0083	(4.38)	0.0027	(2.66)

Panel B: No Rebalancing

Decomposition of IM(1,1) Profits: Value-Weighted Industries

	Size (market capitalization)				$Vol (trading volume)			
Quintiles	Raw	%	DGTW	%	Raw	%	DGTW	%
(*low*) 1	0.000098	0.92%	0.000025	0.60%	0.000258	2.45%	0.000089	2.14%
2	0.000251	2.36%	0.000078	1.83%	0.000952	9.03%	0.000223	5.33%
3	0.000646	6.07%	0.000251	5.91%	0.001141	10.82%	0.000439	10.52%
4	0.001629	15.30%	0.000627	14.73%	0.002898	27.49%	0.000808	19.36%
(*high*) 5	0.008024	75.35%	0.003273	76.94%	0.005293	50.21%	0.002616	62.65%
Total:	0.010651		0.004256		0.010542		0.004175	

This does not mean, of course, that the lead-lag effect has mysteriously disappeared from our data. Notice that if we restrict securities to the *smallest* 20 percent of stocks within each industry, we find that profits substantially increase (as shown in Table V, Panel A), indicating that small firm returns lag those of large firms. As the table 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 effect on the IM(1,1) profits is minimal. Panel B of Table V decomposes the profits from the IM(1,1) strategy into size quintiles as described above. Specifically, we restrict industries to only contain stocks within a particular size quintile, and we compute the profits assuming that the holding period returns are only computed from stocks within that particular size category. As before, the winning and losing industries are still determined by the entire set of stocks in the industry in the previous period, so that the same industries are selected for our IM 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 V demonstrates, the smallest stocks contribute only 0.92 percent to total value-weighted profits, but the largest stocks generate more than 75 percent of these profits. Controlling for size, BE/ME, and individual stock momentum via the DGTW return adjustment, the picture is even clearer because the size premium no longer confounds the influence of small stocks, and, not surprisingly, the contribution of small stocks to adjusted profits is even weaker, at only 0.60 percent, while the largest stocks contribute 76.94 percent of the profits. This result is not surprising since stocks within an industry are value weighted, and it reconfirms our earlier intuition that value weighting largely alleviates the impact of lead-lag effects on profits.[22]

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 $t - 1$) instead of size. Table V reports the raw and DGTW-adjusted industry momentum profits for the largest and smallest trading volume stocks, employing value-weighted industries. As the table shows, the largest dollar trading volume stocks generate *more* profits than the smallest $Vol stocks. Likewise, when we decompose the IM(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

[22] We also run 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, are more pronounced when equal weighting is employed, but the magnitude of this influence is still too small to explain any significant portion of momentum profits.

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.[23]

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

This evidence answers concerns raised by Grundy and Martin (1999) pertaining to the potential influence of lead-lag effects on our industry momentum profits. We demonstrate conclusively that the strong industry momentum phenomenon is virtually unaffected by lead-lag effects due to size, liquidity, or microstructure effects. However, as Grundy and Martin (1999) point out, there may be other lead-lag relations among stocks within an industry that drive momentum. Again, this is almost tautological. The nature of the relation among stocks within an industry that generates positive return autocorrelation is an open question that warrants further study. Our point is that this relation is not due to size or microstructure effects, and thus that industry momentum is not a spurious finding.

V. The Cross Section of Expected Returns and the Interaction between Individual Stock and Industry Momentum

This section 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 the cross section of expected stock returns. This analysis also provides a robustness check on our results, since the regressions employ all securities (i.e., no breakpoint specification is needed), and allow us to control for potentially confounding microstructure effects, to examine the interaction between different momentum horizons simultaneously, and to avoid weighting stocks based on size. Specifically, we regress the cross section of stock returns at time t, adjusted for the return effects of size and BE/ME characteristics (with the Daniel and Titman (1997) procedure described earlier in the paper), on a constant and a host of firm characteristics.[24] We include size and BE/ME attributes as regressors in order to more fully purge the cross section from any confounding influences.

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

[24] Previous evidence indicates that momentum profits may be affected by size and BE/ME. Thus, we adjust returns for these two effects by subtracting the returns of matched-characteristic portfolios. The use of characteristic-adjusted returns eliminates cross-sectional dispersion related to market β's (as noted earlier), 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,[25] size (log of market capitalization at $t-1$), BE/ME (log of 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 VI, along with their time-series t-statistics, computed in the same manner as Fama and MacBeth (1973). The results from these regressions confirm previous findings and provide a benchmark for other regressions. The one-month past return controls for liquidity and microstructure effects documented by Jegadeesh (1990) which induce a reversal in short-term individual stock returns. The long-run return captures the DeBondt and Thaler (1985) three- to five-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 (1999), Carhart (1997), and Fama and French (1996)), and the (12,12) strategy, which we employ for robustness (which is also analyzed in Jegadeesh and Titman (1993)). Incorporating the (12,1) strategy entails replacing $ret_{-6:-1}$ with $ret_{-12:-1}$ in each of the previous regressions. Accommodating the (6,6) and (12,12) strategies is more complex, since these strategies are themselves equal-weighted averages of six and 12 individual 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 $t-6, \ldots, t-6$ 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 VI, Panel A, reaffirms previous findings in the literature: There is a strong short-term (one-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 (such as Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999)). However, while

[25] Market βs 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 run it both ways and obtain similar results.

$ret_{-36:-13}$ appears statistically significant, its economic significance is small.[26] 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 one-month return, confirming our previous intuition that these strategies are uncontaminated by any potential short-term effects due to microstructure or liquidity. However, because 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, $ret_{-36:-13}$, is included as a regressor, the (12,12) strategy becomes significant.

We also run 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 this paper: There is a very strong short-term (one-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-statistics = 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 results in part from the strength of the one-month effect. Finally, the (12,12) strategy is initially marginally insignificant, and is then weakened substantially by controlling for the one-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 VI, Panel C, show that industry momentum at six months subsumes individual stock momentum at six months for both the (6,1) and (6,6) strategies. This is consistent with previous evidence in the paper. Furthermore, the one-month industry momentum variable substantially reduces the industry six-month variable. Hence, one-month industry momentum also drives a significant portion of six-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

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

Table VI

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 January 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 is 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 is 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 is 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 formation and holding period. 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*), (12,2), and (12,12*), where the (6,6*) strategy is an equal-weighted average of five past six-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 is 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.

Strategy (L,H)	Cross-Section of Expected Size- and BE/ME-Adjusted Returns								
	$\hat{\beta}$	ln(Size)	BE/ME	$ret_{-L:-H}$	$ret_{-1:-1}$	$ret_{-36:-13}$	$ind_{-L:-H}$	$ind_{-1:-1}$	$ind_{-36:-13}$
				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)			
				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	0.1457	−0.0011
	(0.15)	(0.23)	(1.50)				(2.84)	(9.11)	(−1.24)

Table VI—*Continued*

	Cross-Section of Expected Size- and BE/ME-Adjusted Returns								
Strategy (L,H)	$\hat{\beta}$	ln(Size)	BE/ME	$ret_{-L:-H}$	$ret_{-1:-1}$	$ret_{-36:-13}$	$ind_{-L:-H}$	$ind_{-1:-1}$	$ind_{-36:-13}$
Panel B: Industry Momentum									
(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)
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)

Strategy (L,H)	$\hat{\beta}$	ln(Size)	BE/ME	$ret_{-L:-H}$	$ret_{-1:-1}$	$ret_{-36:-13}$	$ind_{-L:-H}$	$ind_{-1:-1}$	$ind_{-36:-13}$
	Cross-Section of Expected Size- and BE/ME-Adjusted Returns								
	Panel D: Individual Stock and Industry Momentum (Month Skipped)								
(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)
(12,2)	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)

momentum—the past one-month, six-month, and 12-month returns of the industry—but only one horizon seems to have importance for individual stock momentum once we control for industry momentum—the past one-year return of the individual stock itself.

Finally, even though our previous regressions controlled for the one-month individual stock return and industry return effects, we also skip a month between the formation and holding period for all past return variables in Panel D. The regressions are identical to those in Panel C except that the nearest month's return is excluded. Thus, $ret_{-6:-1}$ becomes $ret_{-7:+2}$ and $ret_{-6:+6}$ becomes an equal-weighted average of *five* past return strategies (i.e., excluding the return from $t-6$ to $t-1$). The 12-month horizon and industry variables are defined similarly. The results, however, 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. Again, the only strategy that retains any significance for individual stock momentum is the one-year strategy (in this case (12,2) since we skip a month).

Thus, even skipping the closest month's return, the only individual stock momentum variable of any significance (among four different strategies) is the 12-month strategy. Conversely, *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. This provides strong evidence affirming the robustness of our results.

VI. 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 almost entirely. These findings are robust to several specifications and treatments and offer important practical insights on the profitability of momentum investment. For instance, these results indicate that momentum strategies are, in fact, not very well diversified because the winners and losers tend to be from the same industry. Moreover, if one were to trade on momentum, industry-based strategies appear to be more profitable and more implementable. Industry momentum generates as much or more of its profits on the buy side than on the sell side, unlike individual stock momentum strategies, which seem to be driven mostly on the sell side. Moreover, unlike individual stock momentum, industry momentum profits remain strong among the largest, most liquid stocks.

The robustness of industry momentum is impressive. Industry momentum is never subsumed by individual stock momentum and consistently subsumes individual stock momentum at every horizon except the (12,1) strategy. 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 (1999) claim that much of the one-year individual stock momentum strategy's profitability is due to tax-loss selling at the end of the year. Thus, industry momentum may be the key element in understanding return persistence anomalies, and it has yet to be incorporated into theoretical models that address this phenomenon.

Of course, these results beg the question: Why industries? This paper presents a great deal of evidence documenting a strong and robust industry momentum phenomenon, but we do not state why such an effect might or should exist. For instance, we know that there are hot and cold IPO markets, and hot and cold sectors of the economy, and investors may simply herd toward (away from) these hot (cold) industries and sectors, causing price pressure that could create return persistence. The recent attraction to Internet stocks is perhaps the latest manifestation of such behavior, which is not unlike a similar pattern in biotechnology firms witnessed years ago.

Several recent behavioral theories proposed by Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999) may provide insight to this phenomenon. Taking the Daniel et al. (1998) model for example, where investors exhibit overconfidence and self-attribution biases, these investors may exhibit more overconfidence and self-attribution in certain types of industries over time. The difficulty in assessing the value of new or changing industries may cause greater overconfidence among investors who are employed in these sectors or have avocations related to these sectors, which exaggerates industry mispricing. Alternatively, under the Barberis et al. (1998) model, investors exhibit a conservatism bias. Thus, when new information arrives, investors may be more conservative in updating their priors about new or changing industries, causing underreaction in industry prices to public information. However, under the Barberis et al. model, investors also exhibit the representativeness bias, causing them to become too optimistic (pessimistic) about firms with a sequence of good (bad) news. If these investors focus on industry rather than firm-specific news, this may cause them to extrapolate performance too far for the industry as a whole, producing long-run reversals in industry returns as well.

Offering yet another behavioral interpretation of return persistence and reversals, Hong and Stein (1999) suggest that slow information diffusion into prices causes an initial underreaction to news, but the presence of "momentum traders" seeking to exploit the slow price movement causes subsequent reversals. In subsequent empirical work, Hong et al. (1999) find that momentum is stronger among small firms with low analyst coverage, which they suggest is a proxy for firms with slow information diffusion. Also, it may take time for news to disseminate among firms in an industry. Industry leaders (generally larger, more followed firms) might be the first to receive a piece of information, but this information may slowly diffuse to other firms within the industry as analysts and investors interpret the potential impact of the signal for the industry as a whole. This could create the kind of lead-lag effects among industry leaders and other firms within the industry (that are unrelated to microstructure or delayed common factor responses) that may be generating momentum.

There are other rational explanations that may be consistent with our findings. For instance, Berk, Green, and Naik (1999) demonstrate that changes in a firm's growth options that are related to its systematic risk can generate momentum in its returns. Since growth opportunities are likely more correlated among firms within industries versus across industries, and likely depend on industry-specific attributes, it is conceivable that their model would generate industry momentum. Similarly, Kogan (1999) obtains positive return persistence under a rational model with irreversible investment, where industry or sector shocks might play a role in the firm's changing systematic risk and expected returns. Intra-industry investment tends to be correlated across firms. Analyzing the extent of growth opportunities or the degree to which industries are faced with irreversible or lumpy investment may shed light on the validity of these potential explanations.

Finally, although we focus on industry membership for our grouping of firms, there are other plausible groupings that might be equally or even more effective in our analysis. We choose industries as the unit of analysis because firms within an industry tend to be highly correlated; they operate in the same regulatory environment, exhibit similar behavior in the corporate finance arena, are similarly sensitive to macroeconomic shocks, and are exposed to similar supply and demand fluctuations. Thus, although asset pricing has failed to establish a significant role for industries in the unconditional setting, this paper identifies a new *conditional* role for industries in asset prices that may be linked to investor behavior, risk, and an extensive line of corporate finance research. Differentiating among these various explanations may prove to be a fruitful area of academic research. For now, however, we leave these potential explanations as preliminary conjectures that warrant further inquiry.

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