Predicting Stock Returns Using Industry-Relative Firm Characteristics[1]

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Abstract

Better proxies for the information about future returns contained in firm characteristics such as size, book-to-market equity, cash flow-to-price, percent change in employees, and various past return measures are obtained by breaking these explanatory variables into two industry-related components. The components represent (1) the difference between firms' own characteristics and the average characteristics of their industries (within-industry variables), and (2) the average characteristics of firms' industries (across-industry variables). Each variable is reliably priced within-industry and measuring the variables within-industry produces more precise estimates than measuring the variables in their more common form. Contrary to Moskowitz and Grinblatt [1999], we find that within-industry momentum (i.e., the firm's past return less the industry average return) has predictive power for the firm's stock return beyond that captured by across-industry momentum. We also document a significant short-term (one-month) industry momentum effect which remains strongly significant when we restrict the sample to only the most liquid firms.

1 Introduction.

The theory of asset pricing attributed to Sharpe [1964] and Linter [1965] is an empirical failure. Beta does not suffice, nor even help, to explain the cross-section of realized stock returns (Fama and French [1992].) In contrast, variables unrelated to existing theory such as market equity (ME) (Banz [1981]), book-to-market equity (BE/ME) (Rosenberg, Reid and Lanstein [1985]), cash flow-to-price (C/P) (Lakonishok, Shleifer, and Vishny [1994]), and past returns (DeBondt and Thaler [1985] , Jegadeesh and Titman [1993], Moskowitz and Grinblatt [1999], and Asness [1997]) possess significant explanatory power.

In this paper we test whether a better proxy for the information about future returns contained in each variable is obtained by breaking the variable into two industry-related components. The first component represents the difference between firms' market-wide characteristics (e.g., their BE/ME ratios) and the average characteristics of their industries (e.g. the average BE/ME ratios of their industries.) We call this a within-industry variable (Goodman and Peavy [1983], Cohen and Polk [1998].) The second component represents the average characteristic of the firm's industry. We call this an across-industry variable.

There may be several advantages to our within-industry and across-industry decomposition. First, measuring variables relative to their industry averages may reduce measurement error. For example, differences in accounting practices across industries can lead to differences in a variable that are unrelated to future returns. Second, a firm's risk and related probability of earning economic rents may be more a function of the firm's position within its industry than its position relative to all firms in the economy with publicly traded equity (Bain [1951], Collins and Preston [1969].) Third, portfolios formed by sorting stocks on within-industry variables are more diversified with respect to industry representation than portfolios formed by sorting stocks on market-wide variables. For example, industry concentration within book-to-market portfolios may be a source of uncompensated return variance. In summary, if the information in a variable is best measured as the difference from its industry mean, measuring that variable as the difference from the sample mean, as is implicit in the OLS framework, will reduce the power of the variable to explain cross-sectional differences in returns.

On the other hand, analysis of our industry components may offer no advantage over the standard approach. The variables we examine may have explanatory power unrelated to industry classification. If a variable is priced independently of industry, subtracting its industry mean throws away information.

To formally examine the importance of within-industry and across-industry variables in expected stock returns we start with the standard Fama-MacBeth (FM) [1973] cross-sectional regression specification:

$$R_{it} = \gamma_{At} + \gamma_{Bt} X_{it} + \varepsilon_{it} \tag{1}$$

where R_{it} is the return on firm i in month t, X_{it} is firm $i's$ market-wide characteristic, and γ_{At} and γ_{Bt} are regression coefficients. We modify this specification to:

$$R_{it} = \gamma_{0t} + \gamma_{1t} X_{Iit} + \gamma_{2t} \left(X_{it} - X_{Iit} \right) + \varepsilon_{it} \tag{2}$$

where X_{Iit} is the equally weighted average characteristic of the firms in firm i's industry. For example, X may be the firm's book-to-market ratio. In equation (1), the significance of the time-series average of $\widehat{\gamma}_{Bt}, \overline{\widehat{\gamma}}_{Bt}$, provides the classic FM test of whether expected returns are unconditionally related to the book-to-market ratio. In equation (2), the significance of $\overline{\widehat{\gamma}}_{1t}$ tests whether firms in distressed (or "value") industries have higher expected return than firms in growth industries. The significance of $\overline{\overline{\gamma}}_{2t}$ tests whether firms that look distressed relative to their industry have higher expected returns than those that look like growth firms relative to their industry, independent of the industry's average book-to-market ratio. We refer to X_{it} as the market wide measure of variable X, the average value of variable X for all firms within firm $i's$ industry, X_{Iit}, as the across-industry measure of variable X, and the deviation from the industry mean, $(X_{it} - X_{Iit})$, as the within-industry measure.

In general our FM tests demonstrate that measuring variables within-industry provides coefficients of somewhat larger magnitude than the market-wide regressions and with smaller standard errors. Note that for all variables except one of the past return variables, the coefficients are of greater magnitude and the standard errors are smaller resulting in higher absolute t-statistics.

We also introduce a new measure of distress: percent change in employees over the most recent year (ΔEMP)[1]. We hypothesize that firms which have recently cut employees are more likely to be distressed, and thus have higher expected returns, than firms which have recently added employees[2]. Cross-sectional FM tests strongly support our hypothesis. Using percent change in employees may provide a significant advantage over using scaled price variables to measure distress. Scaled price variables may explain cross sectional differences in returns because they proxy for distress (or some other source of nondiversifiable risk) or because they measure the existence of a systematic mispricing (a "fad".) Unless managers misestimate growth opportunities in the same

[1] Eugene Fama motivated this variable with discussion about the possible differences in hedging concerns of employees of high BE/ME vs. low BE/ME firms.

[2] Reported results make no correction for change in employees due to merger activity. Dropping firm-years in which aquired firms' assets are at least 10% of total assests, or if this data is unavailable dropping the firm if gross assets increase by more than 50%, strengthen our results.

way as investors, employee growth rates should have a lower correlation with valuation errors made by investors than measures which directly include the market value of equity.

Across-industry and within-industry effects are also present in the power of past stock returns to explain future stock returns. We examine three past return specifications: PAST(13,60) - the average monthly return on a firm's common stock for the sixty months preceding month t not including the twelve months preceding month t; PAST(2,12) - the average monthly return over the preceding 12 months not including the month immediately prior; and PAST(1,1) - the return on a firm's common stock for the month preceding month t. Throughout the paper, we refer to strategies that involve buying winners and selling losers as "continuation" or "momentum" strategies and the strategy of buying losers and selling winners as "contrarian."

We confirm the strong long-term contrarian effect, PAST(13,60) and show that it consists of a weak across-industry contrarian effect and a strong within-industry contrarian effect. Expected returns are higher for long-term loser industries than long-term winner industries, and higher for long-term within-industry losers than long-term within-industry winners.

We also confirm the strong one-year market-wide momentum (or continuation) effect, PAST(2,12), studied by Jegadeesh and Titman [1993] and Asness [1997] and show that it consists of a strong within-industry momentum effect and a strong across-industry momentum effect. This is in contrast to the results reported by Moskowitz and Grinblatt [1999] who find that momentum effects are due almost entirely to across-industry effects. We find that expected returns are higher for last year's within-industry winners than last year's within-industry losers and confirm the effect of Moskowitz and Grinblatt that returns are higher for last year's winner industries than last year's loser industries. In fact, PAST(2,12) is the only variable in our FM tests that has a lower p-value across-industry than either within-industry or market-wide, although this result reverses in value-weighted tests.

We also document significant market-wide, within-industry, and across-industry PAST(1,1) effects. However, these results are partly driven by market microstructure issues related to the combined forces of bid-ask bounce and non-synchronous trading. We conclude that the market-wide and within-industry contrarian power of PAST(1,1) is probably spurious, but the momentum effect of across-industry PAST(1,1) remains significant even after we restrict the sample to only the most liquid firms.

Finally, we devise a test of whether within-industry measurement yields a statistically significant improvement over market-wide measurement. We compare the average return on a long-short portfolio formed on a variable measured market-wide with the average return on a long-short portfolio formed on the same variable measured within-industry. To make this comparison meaningful we compare long-short portfolios with equal volatility. We find that for almost every variable the average spread in returns is of larger magnitude when measured within-industry although the improvement is generally statistically insignificant.

The paper proceeds as follows: Section 2 describes the data. Section 3 examines our specifications in equation (1) and equation (2) using the FM methodology. Section 4 measures the difference in statistical and economic significance between portfolios formed on within-industry and market-wide variables. Section 5 assesses the power of across-industry PAST(1,1) within size and trading volume deciles. Section 6 examines the effect of across-industry and within-industry momentum using 6 month buy and hold portfolios. In section 7 we summarize, discuss future research, and consider open questions.

2 Data

Our initial sample includes all firms listed on the NYSE, AMEX, and Nasdaq stock exchanges from July 1963 (1973 for Nasdaq firms) through December 1998. We omit firms with negative book values, firms with missing returns, and to mitigate survivorship bias we omit any firm without at least two prior years of Compustat data.

We assign firms to industries using the classification scheme of Fama and French [1997]. Each month, the four-digit SIC code of each available NYSE, AMEX, and Nasdaq stock determines its placement in one of 48 industries. Appendix 1, which is identical to that in Fama and French [1997], lists the range of SIC codes that define each industry.

Table 1a shows the value-weighed average monthly return, standard deviation , average number of firms, and average total market capitalization of each industry sorted by average return. The top performing industries were Tobacco Products(1.63%/month), Candy & Soda (1.50%),Miscellaneous (1.48%), Entertainment (1.48%), and Medical Equipment (1.46%). The poorest performing industries were Fabricated Products (0.65%), Steel Works (0.72%), Utilities (0.86%), Machinery (0.92%), and Chemicals (0.98%). The monthly standard deviations of the value-weighted industry portfolios range from highs of 10.69% (Miscellaneous) and 10.22% (Precious Metals) to lows of 3.91% (Utilities) and 4.41% (Telecommunications). Note that the average industry in an average month contained 54 firms with an average industry market capitalization of over $41 billion (in current dollars.)

At the end of every June, we calculate the book-to-market ratio (BE/ME) and cash flow to price (C(+)/P[3]) from each firm's prior end of December market value of equity and their prior

[3] C(+) refers to firms with positive cash flows. We use these firms to calculate our industry averages. In our regression tests, we include a dummy variable to distinguish firms with negative cash flows.

year's book value and cash flow. BE/ME and C(+)/P are updated annually. ΔEMP is formed analogously (but requires no ME adjustment). Thus, there is at least a six month lag between the actual date of the information and the date we use the information. This December to June lag insures that the accounting data would actually be available at the time portfolios are formed.[4] Each month, each industry ratio equals the equally weighted average of the ratios of the industry's constituents. We require industry averages to be calculated from a minimum of three firm-years of data[5]. Table 1b shows the time-series average, median, minimum, and maximum of BE/ME, C(+)/P, and ΔEMP for each industry. All calculations in table 1b use the longest time-series available for each industry.

Table 1b sorts industries on their average BE/ME. As pointed out by Fama and French [1997], low average BE/ME industries tend to be growth industries, and high average BE/ME industries tend to have had relatively poor times over the prior periods. The numbers in the C(+)/P and ΔEMP columns support this analysis. The ten industries with the lowest average BE/ME have an average C(+)/P of 7% and an average ΔEMP of 10%. In contrast, the ten industries with the highest average BE/ME have an average C(+)/P of 15% and ΔEMP of 5%.

Table 1b also shows the impressive range of each variable. For example, although the average industry's average BE/ME is 0.70, the average industry had a low BE/ME of 0.29 and a high BE/ME of 1.59. Looking at the minimum and maximum values industry by industry, we see that at some point, virtually every industry looked unmistakably like either a growth industry (very low BE/ME) or a value industry (very high BE/ME). In addition, we see that the average industry

[4] We also follow this procedure in our cross-sectional regressions and portfolio sorts that involve BE/ME, C/P, or ΔEMP. In contrast, ME and each of our past return variables are based on their values as of the end of the previous month.

[5] Forty of forty-eight industries have the required minimum of three firms for the entire 426 months. The shortest time series is 219 months (Miscellaneous) and the average time series length is 414 months.

generates average cash flow of slightly less than an eighth of its market value, but this ratio ranges from 0 % to 24% through time. At some point 30 of 48 industries had cash flow of at least 20% of market value, 8 had cash flow of a third of market value, and 26 had cash flow less than or equal to 3% of market value.

The ranges of ΔEMP are perhaps the most interesting. The average change in the workforce of the firms in an industry increases by, on average, about 8% per year[6]. However, a look down the minimum/maximum column reveals that at some point every industry has been far above and far below this average. In fact, 45 industries had at least one year in which employment dropped and 31 suffered cuts of more than 5%. On the growth side, 36 industries enjoyed at least one year of more than 25% employment growth.

Taken together, our evidence for BE/ME, C(+)/P and ΔEMP strongly supports the story and evidence of Fama and French [1997] that industries move dynamically between growth and distress. In fact, every industry had at least one period above and below the market average BE/ME, C(+)/P, or ΔEMP of that period. By focusing on only BE/ME, Fama and French [1997] may actually understate the industry dynamics of growth and distress.

Our specifications of past stock returns are defined as the arithmetic average of a firm's monthly stock return over some earlier period: $PAST_{i,t}(x,y) = \sum_{\tau=t-x}^{t-y} R_{i,\tau}/(y-x+1)$. For example, PAST(2,12) is the average monthly return on a firm's common stock for the year preceding month t not including the month preceding month t.

The information in table 1 only hints at the time-series properties of the cross-section of these variables (i.e., the spread across industries of the industry averages each month.) If a variable

[6] Removing firm-year observations in which acquired firm's assets are at least 10% of total assets results in a mean (median) ΔEMP of 0.07 (0.05).

fails to produce a spread across industries, our across-industry measure has no hope of containing information about expected returns. We can report that BE/ME, C(+)/P, and ΔEMP regularly produce large cross-sectional spreads in their equally-weighted industry averages:

1. log(BE/ME) has an average across-industry cross-sectional standard deviation of 0.35 and an average range of 1.58.

2. C(+)/P has an average across-industry cross-sectional standard deviation of 0.04 and average range of 0.20.

3. ΔEMP has an average across-industry cross-sectional standard deviation of 9% and an average range of 48%.

The mean cross-sectional spread and standard deviation in value-weighted industry averages is larger for each variable reported. This is due to the effect of outliers receiving large weights. For example, in the last month of 1998 the industry with the lowest employment growth was Defense with an equally weighted industry average growth rate of 0.9% and a value-weighted growth rate of -6.4%. The difference is due to a single firm, Lockheed-Martin, which comprised 83% of the industry by market capitalization which had employee growth of -7.4%.

This cross-sectional evidence and the information in table 1b highlight the potential importance of our specification in equation (2) for two reasons. First, our across-industry measure will evaluate the connection, if any, between returns and what we now know are large cross-sectional differences in the industry average characteristics. Second, our within-industry measure, which "nets-out" the sometimes extreme cross-sectional variance in the industry averages, will evaluate the importance, if any, of adjusting by subtracting the industry averages.

3 Single Variable Analysis

3.1 Fama-MacBeth Regressions

We next evaluate the power of within-industry and across-industry variables to explain the cross-section of stock returns. To compare our industry measures to the standard specification of equation (1), table 2 shows the average slopes and t-statistics from equation (1) and equation (2) for each variable.

3.1.1 Market Equity (ME)

Although the market-wide market value of equity, log(ME), is reliably priced (Banz [1981] , Fama and French [1992]), within-industry log(ME) provides a better measure of the effect of size. The average within-industry price (-.20) is slightly larger in magnitude than the average market wide price (-0.18), while the within-industry t-statistic (-4.28) is further from zero than the market-wide t-statistic (-3.68). Thus, the "small firm effect" is slightly more consistent when ME is adjusted for industry differences. The t-statistic on across-industry log (ME), -0.45, suggests that industry differences in average log(ME) cannot reliably explain cross-sectional differences in average returns. At best, the "small industry effect", or the price effect of industries where the average firm size is small, is weak over our sample period.

A respecification of equation (2) provides a simple test of whether the coefficient on the within-industry variable is significantly different from that on the across-industry variable. Note that equation (2) is identical to:

$$R_{it} = \gamma_{0t} + (\gamma_{1t} - \gamma_{2t})X_{Iit} + \gamma_{2t}X_{it} + \varepsilon_{it}. \tag{3}$$

The coefficient on the log of market capitalization and the associated t-statistic are the same as that of our within-industry measure in equation (2), but the coefficient on the average market capitalization of the industry is the difference between the across-industry and within-industry measures in equation (2). The value of $(\gamma_{1t} - \gamma_{2t})$, 0.16, is statistically significant (t-statistic of 2.43). The within-industry effect is significantly larger (more negative) than the across-industry effect.

Omitting January observations has the expected effect of drastically reducing the magnitude and significance of the coefficients. In unreported regressions, the magnitude of the coefficient on market-wide log size falls from -0.18 to an insignificant -0.03. The within-industry coefficient is similarly reduced from -0.20 to an insignificant -0.05 but the across-industry reverses sign, changing from -0.04 to 0.15 (with a t-statistic of 1.74). Surprisingly the results from specification (3) reject that the within-industry and across-industry coefficients are equal even in non-January months ($\gamma_{1t} - \gamma_{2t} = 0.20$, t-statistic 2.98).

3.1.2 BE/ME

Like market value of equity, the market-wide version of the book-to-market ratio (log(BE/ME)) is reliably priced (Stattman [1980], Rosenberg, Reid, and Lanstein [1985], DeBondt and Thaler [1987], and Fama and French [1992]), but the within-industry version provides a better measure of the relationship between book-to-market ratios and stock returns. The average within-industry slope (0.54) is marginally larger than the average market-wide slope (0.49), while the within-industry t-statistic (9.27) is larger than the market-wide t-statistic (6.98). Thus, the spread in average returns of high BE/ME firms over low BE/ME firms is more consistently positive when BE/ME is adjusted for industry differences. The small and insignificant coefficient on the across-industry variable suggests that industry differences in book-to-market are only marginally able to explain cross sectional differences in firm stock returns.

The estimates from equation (3) show that the difference between the across-industry coefficient and the within-industry coefficient is statistically significant. The difference of -0.35 has a t-statistic of -2.54.

3.1.3 C/P

Confirming earlier results (Lakonishok, Shleifer, and Vishny [1994]), we find that expected returns are a U-shaped function of the cash flow-to-price ratio. High cash flow-to-price and negative cash flow-to-price firms have higher returns than low but positive cash flow-to-price firms and, like size and book-to-market, cash flow-to-price effects are more precisely measured within-industry than market-wide. C(+)/P's average within-industry slope (2.38) is marginally higher than its average market-wide slope (2.29) and its t-statistic is higher (5.66 vs. 4.59). Thus, the spread in average returns of high C(+)/P firms over low C(+)/P firms is more consistently positive when C(+)/P is adjusted for industry differences. The results from specification (3) show that although the difference in coefficients is large in magnitude, the within-industry coefficient is over three times the size of the across-industry coefficient, the difference of -1.69 is not statistically significant.

3.1.4 ΔEMP

We introduce a new, easily measured proxy for distress: percent change in employees over the most recent year. Our hypothesis is that firms which have recently cut employees are more likely to be distressed, and thus have higher expected returns, than firms which have recently added employees. Note that ΔEMP, unlike other measures of distress such as BE/ME and C/P, is not scaled by price and as a result may capture an independent aspect of distress.

We find evidence consistent with a distress story for ΔEMP. Measured market-wide, ΔEMP has an average coefficient of -0.58 and a t-static of -4.94. Low (or negative) ΔEMP firms do, in fact, have reliably higher average returns than high ΔEMP firms. Our within-industry analysis suggests an even stronger connection between recent employment trends and average returns. The average price of our within-industry measure of ΔEMP moves to -0.67 while the t-static jumps to -6.86[7]. The difference between the within- and across-industry coefficients is both large in magnitude and statistically significant (t-statistic = 2.67).

3.1.5 Past Returns

Our results on the power of past returns to characterize the cross-section of expected stock returns extends the work of Asness [1997]. The long-term contrarian effect, PAST(13,60), is strong when measured market-wide (average slope of -0.15, t-statistic = -3.61) and is measured slightly more precisely when measured within-industry (average slope =-0.15, t-statistic -4.18). Across-industry differences in PAST(13,60) are measured with less precision (average slope -0.16, t-static = −1.59). If PAST(13,60) captures a similar aspect of distress as the book-to-market ratio and cash flow-to-price ratio, the within-industry results of using PAST(13,60) to explain future stock return is not surprising in light of our earlier results. Interestingly, the across-industry result using the regression equation (3) shows no significant difference between the within-industry coefficient and the across-industry coefficient.

The continuation effect, PAST(2,12), represents our only variable with less power within-

[7] Omitting firms likely to have been engaged in merger activity in the prior year has little impact on our results. The average price of our intra-industry measure of ΔEMP is -0.79 (t-statistic = -6.90) compared to a market-wide price of -0.68 (t-statistic = -4.87).

industry (average slope 0.04, t-statistic = 3.40) than market-wide (average slope = 0.06, t-statistic = 4.15). However, this decrease in power is driven by a strong across-industry continuation effect (average slope = 0.30, t-statistic = 6.28). Like individual stocks, winning industries over the past year have higher expected returns than losing industries.

Moskowitz and Grinblatt [1999] find that once adjusted for industry effects, momentum profits from individual equities are significantly weaker and for the most part are statistically insignificant. We disagree and find significant profits to within-industry momentum. The results from specification (3) show the difference in coefficients on within-industry and across-industry momentum variables of 0.26 to be significant with a t-statistic of 6.29. We find two major differences in methodology which may explain the differences in results. First, Moskowitz and Grinblatt define industries based on two digit SIC codes yielding 20 industry classes defined in their table 1. Two digit SIC codes often include widely disparate lines of business which will mask the importance of differences from industry means. For example, SIC code 37, Transport Equipment, includes defense contractors (guided missiles and space vehicles [3760-3769] and tanks [3795]), aircraft manufacturers [3720-3728], ship builders [3730-3731], and railroad equipment [3740-3743], but excludes automotive industry subcontractors such as tire cord and fabric [2296] and auto trim [2396] both of which are considered "apparel." We believe the industry classification scheme used in Fama and French [1997] will produce more reliable measures of industry effects. Second, these authors form portfolios based on the return over a period including the previous month. As shown in our table 2, the across-industry effect is of the same sign for both PAST(1,1) and PAST(2,12) but the within-industry effect is of opposite sign. Forming portfolios based on PAST(1,6), as in Moskowitz and Grinblatt, would thus mask the within-industry continuation effect. To make matters worse, the contrarian within-industry effect at one month horizons appears to be very susceptible to market microstructure issues. As we will see in section 3.2, value-weighted portfolio tests lead to an even stronger conclusion that within-industry momentum has power and, in this test, has more power than across-industry momentum. Finally, in section 6 we directly examine the effects of these differences in method.

We also present results for a variable whose large market-wide, within-industry, and across-industry significance can partly be attributed to market microstructure issues. PAST(1,1) has a market-wide average slope of -0.05 and a t-statistic of -11.69. In other words, market-wide one month contrarian strategies are statistically powerful. Its within-industry average slope grows to -0.07 while its t-statistic jumps to -16.39. Interestingly, this contrarian nature of market-wide PAST(1,1) hides a strong continuation effect at the across-industry level (average slope = 0.19, t-statistic = 10.87). These mixed results may be partly spurious and a function of the combined forces of bid-ask bounce and non-synchronous trading. Bid-ask bounce can affect the market-wide and within-industry results as the power of contrarian strategies is exaggerated in empirical tests which buy poor performers at the bid and sell strong performers at the offer. Non-synchronous trading can exaggerate the across-industry continuation results as firms that did not trade "catch up" with their industries[8]. Our explanation involving microstructure is taken up in section 5. In short, the market-wide and within-industry contrarian results appear largely spurious, but we believe the across-industry momentum results are real.

[8] This is the lead-lag effect documented in Lo and MacKinlay [1990] in which large firm returns lead small firm returns.

3.2 Portfolio Sorts

Our results thus far suggest that there may be important differences when measuring variables market-wide vs. within-industry. As a robustness check and to complement our inference from the FM portfolios, we form portfolios using two different weighting schemes. For each variable, we form 2 sets of quintile portfolios by sorting stocks on their (1) market-wide, (2) within-industry, and (3), across-industry characteristics. We then form zero-investment portfolio returns by subtracting the returns on quintiles 1 (Q1) from the returns on quintile 5 (Q5). We form both equal-weighted and value-weighted portfolios. Testing with value-weighted portfolios ensures that our results are not being driven by the smallest firms, and are probably more relevant for most large-scale (i.e., institutional) investors. For the industry measures, the equal-weighted portfolios use equally weighted industry averages, as in our previous FM regressions, while the value-weighted portfolios form within-industry measures by subtracting value-weighted industry averages. The portfolios are rebalanced monthly and each month the sorting information is exactly the same information used in the earlier FM regressions. That is, we take the same steps to insure that the sorting information (e.g., the firms' BE/MEs) is available at the time the portfolios are formed (see section 2). Each month the universe of stocks in the sorted portfolios is exactly the same universe of stocks as in the FM portfolios.

Table 3 contains the results of the market-wide, within-industry, and across-industry sorts for both the equal-weighted and value-weighted portfolios. We report the average return, standard deviation, t-statistic, and the percent of months that the Q5-Q1 zero investment portfolio produced positive returns.

3.2.1 Equally Weighted Portfolios

In general, the results for the equally weighted portfolios bear a strong resemblance to the FM results of section 3.1. With the exception of PAST(2,12), the variables produce their largest (absolute) t-statistic when measured within-industry. For all variables the increased (absolute) t-statistic comes all or in part from reduced standard deviation. As before, PAST(13,60) benefits little from the within-industry adjustment while PAST(1,1) retains its striking statistical significance measured both market-wide and, more so, within-industry.

The across-industry results are also quite similar to those in section 3.1. PAST(2,12) remains the only factor which produces a higher t-statistic measured across-industry than either within-industry or market-wide. Again, we see the strong industry continuation effect of PAST(1,1).

3.2.2 Value-Weighted Portfolios

The general level of statistical significance is lower for the value-weighted portfolios than for the equal-weighted and FM portfolios. ΔEMP, and PAST(13,60) are statistically insignificant both market-wide and within-industry. However, our within-industry variables consistently improve on variables measured market-wide. In fact, six of seven variables produce their largest (absolute) t-statistics within-industry. Since the difference in portfolios weights between value-weighted and equal-weighted portfolios can be very large, we find the robust value-weighted within-industry results supportive of our within-industry and across-industry specification.

Perhaps the most surprising value-weighted results are for PAST(1,1). Measured market-wide, the dramatic drop in the average spread and t-statistics going from equally weighted (average spread and t-statistic) to value-weighted (average spread and t-statistic) is consistent with a microstructure explanation. Bid-ask bounce should impact larger firms less than smaller firms. However, the change from equal-weighting to value-weighting affected the within-industry and across-industry results less than it affected the market-wide results. Value weighted PAST(1,1) has an within-industry t-statistic of -8.16 and an across-industry t-statistic of 5.99. Section 5 further investigates the power of PAST(1,1) within deciles formed by sorting firms on liquidity measures.

4 Market-Wide vs. Within-Industry

Section 3.2 demonstrates that creating portfolios based on within-industry measures generally increases the statistical significance of our results. For example, the test of whether top quintile BE/ME firms have higher average returns than bottom quintile BE/ME firms (value-weighted) produces a t-statistic of 2.48, while the corresponding within-industry test produces a t-statistic of 3.14.

As an additional test of the marginal significance of a within-industry vs. market-wide specification we form equal volatility long-short portfolios. As in section 3.2 we form a long-short portfolio for each variable with the long component consisting of the top quintile firms and the short component consisting of bottom quintile firms (all portfolios in this section are value-weighted.) For each variable we form two separate long-short portfolios based on (1) market-wide measurement and (2) within-industry measurement. We next scale each long-short portfolio such that its realized monthly volatility is 5.00%. For example, the monthly volatility on Q5-Q1 for market wide BE/ME is 3.68% (table 3) so we create a new portfolio that is effectively (5.00%/3.68%) units of the market-wide BE/ME portfolio tested in section 3.2. This levered portfolio is feasible because of the self financing nature of long-short portfolios (ignoring trading costs and leverage restrictions). Thus for each variable we end up with two 5% volatility long-short portfolios based on (1) market-wide measurement and (2) within-industry measurement. Think of these portfolios as equally risky competing trading strategies and because the portfolios have equal volatility (assumed known and equal to 5%), we have a clean statistical test of their average return difference.

Table 4 contains our results. We report the average return, t-statistic, and percentage of months positive for the two separate long-short portfolios (market-wide and within-industry) and a third portfolio which is the difference between the two (within-industry - market-wide). For example, the within-industry ME's average monthly return of -0.50% is 0.03% below the average monthly return of market-wide ME of -0.47% and the t-statistic of this difference is -0.54. Thus, for the same amount of volatility, sorting on within-industry ME instead of market-wide ME produces more average return (small firms outperform large firms by more), but not statistically significantly more average return.

The results for BE/ME and C(+)/P are similar. Our within-industry long-short BE/ME strategy produces a statistically insignificant 0.16% higher average monthly return (t-statistic = 0.94). For C(+)/P our within-industry long-short strategy produces 0.23% higher average monthly return and, like BE/ME, the difference is statistically insignificant (t-statistic = 1.42).

The results for PAST(2,12) are stronger using the within-industry measure and produces a statistically significant difference of 30 basis points per month. However, PAST(1,1) is again off-the-charts. Measured market wide a 5.00% volatility long-short strategy based on PAST(1,1) has an average return of -0.43% per month. Measured within-industry the same volatility strategy has an average monthly return of -1.98%. This difference is highly statistically significant (t-statistic = -11.12).

With the exception of PAST(13,60), every variable we test induces more spread in Q5-Q1 returns, at 5.00% volatility, when measured within-industry than market-wide. However, for only two measures, PAST(1,1) and PAST(2,12), is this improvement statistically significant. If there are systematic differences in variables across industries unrelated to expected return we might expect within-industry measures to improve over market-wide measures. For example, simple differences in accounting methodology across industries could induce misleading and noisy across-industry differences.

5 PAST(1,1) and Liquidity

In tables 2 and 3 we show that the strong contrarian nature of market-wide PAST(1,1) hides an even stronger within-industry contrarian effect and a strong across-industry continuation effect. However, we have noted that PAST(1,1)'s seemingly extreme power to describe the cross-section of stock returns may be spurious. For example, the combined forces of bid-ask bounce (for market-wide and within-industry contrarian strategies) and non-synchronous trading (for across-industry momentum strategies) may drive the results. This hypothesis has testable implications. If correct, PAST(1,1)'s explanatory power should decrease with liquidity. That is, the power of each form of PAST(1,1) should greatly diminish or disappear among the most liquid firms and peak among the most illiquid firms. We test this hypothesis using two simple proxies for liquidity, share trading volume and market value of equity, and examine the effects these measure have on the significance of market-wide, within-industry, and across-industry PAST(1,1).

Trading volume data from Nasdaq and from the NYSE or AMEX are not directly comparable. Virtually every trade on Nasdaq takes place with the dealer whereas on the NYSE, only 20% of trades involve NYSE member firms acting as a principal (including 9% of trades which involve the specialist.) In addition, many Nasdaq trades are between dealers. Gould and Kleidon [1994] report that the average reported volume on Nasdaq should be reduced by 58% to account for these intermediary trades. Reducing NYSE reported volume by 10% (to net out the member firm trades) results in a .42/.90 = .47 or 53% reduction in Nasdaq trading volume to make it comparable to NYSE reported volume. Therefore we divide reported share volume on Nasdaq by 2. Failure to adjust Nasdaq trading volume gives essentially the same results as in Table 5.

Our exercise is as follows:

1. At the end of each month from June 1962-November 1998, we sort all NYSE, AMEX and Nasdaq stocks into deciles based on their share trading volume over the month and their ME. We use NYSE breakpoints to define the volume and ME deciles.

2. Within each decile, we then sort stocks in quintiles based on their market-wide, within-industry, and across-industry return over the month.

3. We value-weight the 50 portfolios that comprise the volume decile/PAST(1,1) quintile intersections and the 50 portfolios that comprise the ME decile/PAST(1,1) quintile intersections. Value-weighted portfolios, as opposed to equally weighted portfolios, give extra weight to larger and presumably more liquid stocks which should further reduce bid-ask bounce and non-synchronous trading problems.

4. We measure the return to each portfolio over the following month and then re-sort.

Table 5 contains our results. Within each volume and ME decile and for each measure of PAST(1,1) we report the average monthly quintile5 - quintile 1 (Q5-Q1) spread, the t-statistic of this average, and the percent of months that the Q5-Q1 spread produced a positive return. The results are clearly consistent with one part of the original hypothesis and clearly inconsistent with the other.

Specifically, they support the bid-ask bounce explanation, but not non-synchronous trading.[9]

5.1 Bid-Ask Bounce

Market-wide PAST(1,1) is strongly significant until about the 7th volume decile (average monthly spread = -0.92 basis points, t-statistic = -3.77) after which the difference in quintile returns becomes statistically insignificant. By the 8th volume decile, market-wide PAST(1,1) is marginally insignificant (t-statistic = -1.68) and among the most highly traded stocks, PAST(1,1) actually becomes a weak continuation effect (average monthly spread = 6 basis points, t-statistic = 0.25). This evidence is consistent with the hypothesis that the incredibly strong contrarian market-wide PAST(1,1) effect in our FM and equally weighted portfolios (tables 2 and 3) is driven at least partly by bid-ask bounce.

For each volume decile, within-industry PAST(1,1) produces a stronger contrarian effect than market-wide PAST(1,1). Among the stocks in the 7th volume decile - stocks that trade on average about 1.7 million shares per month - within-industry PAST(1,1) produces an average monthly spread of 137 basis points and a t-statistic of -6.07. For stocks in the 9th volume decile - stocks that trade on average about 4.1 million shares per month - within-industry PAST(1,1) produces an average monthly spread of 72 basis points and a t-statistic of -3.31. However when we look at the most highly traded stocks, the power of within-industry PAST(1,1) largely goes away. The average monthly spread drops to 40 basis points and the t-statistic drops to -1.85. Thus, like market-wide PAST(1,1), the within-industry PAST(1,1) results may be at lest partly driven by bid-ask bounce and be, therefore,at least partly spurious.[10]

[9] Our description focuses on the volume results. The largely similar ME results in the bottom panel of table 5 provide a robustness check.

[10] In light of PAST(1,1)'s strong significance in the 7th, 8th,and 9th volume deciles - where average volume is very high - it might be tempting to conclude that the intra-industry PAST(1,1) effect is "real." However, the turnover of

5.2 Non-Synchronous Trading

In contrast to our negative indications regarding the true power of market-wide and within-industry PAST(1,1), our results here support the hypothesis that the power of across-industry PAST(1,1) is real and not a result of non-synchronous trading. First, the drop in the average monthly spread from the stocks which trade least (137 basis points per month) to the stocks traded most (102 basis points per month) is tiny in light of the enormous differences in average share trading volume between the lowest and highest deciles. Second, the t-statistic among the highest volume decile is a very significant 3.96. Looking at firms that fall in the top volume decile on the NYSE, a momentum strategy based on across-industry PAST(1,1) induces approximately 102 basis points of monthly return, is strongly statistically significant, and produces a positive monthly return in over 61% of the months we test. We find it difficult to believe that non-synchronous trading is a serious problem among the highest volume decile stocks and certainly not of the order needed to entirely drive our results. The results are considerable stronger for firms not in the highest decile. These surprising results suggest that industry momentum is real at monthly horizons and can be used effectively in the portfolio construction process. Furthermore, the strength of across-industry PAST(1,1) combined with the simplicity of its measurement suggests that reconciling its power with rational pricing represents a challenge for future work.

Q5 and Q1 portfolios is close to 100% each month. Under the most favorable trading conditions, the combined costs of trading commissions and market impact would make these Q5-Q1 average spreads drop near zero or, more likely, go negative.

6 Do Industries Explain Momentum?

Moskowitz and Grinblatt (MG) [1999] claim that momentum based investment strategies are significantly less profitable once we control for industry momentum. We find that both past industry returns (our across-industry momentum variable) and past firm returns relative to the industry mean (our within-industry momentum variable) contain information about future returns. We show in Table 3 that both within-industry and across-industry momentum effects are economically and statistically significant and, when portfolios are value-weighted, that the within-industry effect is three times as large in magnitude.

We believe that the difference in conclusions is at least partly driven by two factors. First, the difference in industry definitions. MG define a set of 20 industries based on two digit SIC codes while we use the set of 48 industries based on 4 digit SIC codes originally defined in Fama and French [1997]. Second, we claim that skipping a month between the portfolio formation period and the holding period is crucial to avoid the market-microstructure issues described above. Further, since the within-industry effect is of opposite sign at short and intermediate horizons while the across-industry effect is of the same sign, failing to skip a month between ranking and portfolio formation will reduce the within-industry effect but not the across-industry effect.

To isolate the effect of the particular set of industry definitions used and the effect of skipping a month between ranking and portfolio formation, we replicate the methodology used in MG using both sets of industry definitions and with and without skipping a month between the measurement period and the holding period. Table 6 contains the results.

The procedure used in MG is similar to that used in Jegadeesh and Titman [1993] and is outlined briefly here. We form winner-loser self financing portfolios by ranking stocks based on their total return during a six month prior period. PAST(1,6) corresponds to ranking stocks based on their t-6 to t-1 total return[11]. This is the ranking criteria focused on by MG. For comparison, we calculate a PAST(2,7) measure which ranks stocks based on their total return over a six month period immediately prior to portfolio formation, but skipping the most recent month. When forming a portfolio of winning stocks with the market-wide or within-industry measure we form a value-weighted portfolio of the highest 30%. Similarly for the losing stocks. In defining a winning industry, we rank total return on value-weighted industry portfolios and use the highest 15% of industries. We repeat this procedure each month.

To avoid test statistics that are based on overlapping returns, we employ the same technique as MG. The holding period return each month is the result of the portfolios formed in months t through t-5. For example, the June 1998 return is 1/6 determined by the rankings on the first of June, 1/6 by the rankings on the first of May, etc.,

6.1 Comparison of Methods.

Table 6 presents our results. PAST(1,6) corresponds to ranking stocks based on the previous six months total return while PAST(2,7) corresponds to a ranking over the previous six months skipping the month immediately prior to the portfolio formation period. Market-wide is the average monthly return to a strategy of buying winners and shorting losers. Ranking based on market-wide PAST(1,6) gives an average monthly return of 43 basis points (t-statistic = 2.46) while ranking on market-wide PAST(2,7) gives an average monthly return of 68 basis points (t-statistic = 4.02).

[11]This is in contrast to the notation in previous sections where PAST(1,6) represents the average monthly return rather than the total return during the previous six months.

Skipping a month between the ranking period and the holding period raises momentum profits by over 50%.

Across-industry refers to the average monthly profit of buying winning value-weighted industry portfolios and shorting losing industry portfolios. "FF Industries" corresponds to the industries defined in appendix 1 and "MG Industries" corresponds to the industries defined in MG, table 1. A winning industry in the FF industry group is an industry whose value-weighted portfolio return over the ranking period is in the top 7 of the 48 industries. A winning industry in the MG industry group is an industry whose value-weighted industry portfolio is in the top 3 of the 20 industries[12]. When ranking on PAST(1,6), changing from the industry definitions used by MG to the industry definitions described in appendix 1 raises average momentum profits from 31 basis points per month to 65 basis points. With either set of industry definitions, moving from a ranking based on PAST(1,6) to a ranking based on PAST(2,7) results in an increase in average monthly profits.

Within-industry results rank stocks based on the difference between the stock return and the value-weighted industry mean. The winning portfolio is a value weighted portfolio of the top 30% of stocks during the ranking period. Within-industry results range from 42 basis points to 61 basis points per month depending on the particular set of industry definitions and ranking variables used, but is significant at the customary 5% level in all cases. Further, we find that momentum profits are higher using our industry definitions and our ranking period. Clearly the choice of industry

[12] The market-wide results for PAST(1,6) are very similar to those reported by Moskowitz and Grinblatt although the industry portfolio results are less strong with the average monthly return not even significant at the 5% level. The difference in industry momentum results may be due to small differences in sample composition (for example, we drop all firms with negative BE/ME) and small differences in the sample period.

definitions and the skipping of a month between ranking and portfolio formation have large impacts on momentum trading profits.

6.2 Two-Way Sorts.

The results in table 6 indicate the importance of industry definitions and of skipping a month between ranking and portfolio formation, but do not address the central point of MG, that momentum profits are primarily due to industry momentum. We illustrate the importance of our within-industry measure by performing a two-way sort based on value-weighted industry portfolios and our within-industry measure. For example, each month we form a value weighted portfolio of all firms that are both in the top 30% of all firms based on total return measured within-industry and in an industry in the top 15% of all industries during the ranking period. The ranking period is PAST(2,7) and we hold each portfolio for six months.

Table 7 contains the results. In each row corresponding to the winner, middle, and loser industries we see that the average return to a portfolio formed on within-industry PAST(2,7) is increasing in within-industry PAST(2,7). Similarly with each column we see increasing holding period return to each industry category. The average monthly return to a strategy of buying winner/winner and shorting loser/loser value-weighted portfolios is 1.38% *per month*, twice the market-wide figure. The trading strategy return is positive in 61.50% of the months in the sample.

Sorting based on returns measured relative to an industry mean may imply long-short positions in small market capitalization stocks. To examine the effect of omitting the smallest firms we calculate the median market capitalization for each industry each month using only those firms listed on the NYSE and AMEX. We then drop all firms whose market capitalization falls below this median value, resulting in the elimination of 70% of the sample (Nasdaq firms with a sufficiently large market capitalization are retained in the sample). We then repeat the two-way sort procedure and report the results in Table 8. Although the average number of firms in each cell has fallen by a large fraction, the average return from a strategy of buying winner/winner stocks and selling loser/loser has only fallen from 1.38% to 1.23% per month while the associated t-statistic has fallen from 4.73 to 4.36. The relatively small impact is due to our use of value-weighted portfolios throughout. It is clear that firm stock return measured relative to the industry mean has information about future stock returns that is not contained in the industry mean.

7 Conclusions and Discussion

Our within-industry and across-industry variables are better able to explain the cross-section of expected stock returns than risk proxies in the more common market-wide form. Perhaps our results are not surprising. If theoretical models of the importance of firms' position within their industries are correct (Bain [1951], Collins and Preston [1969]), our results are potentially consistent with extant theory. In addition, across-industry variation in a variable unrelated to expected returns like that induced by accounting differences across industries may partly drive the success of our within-industry measure. Also note that portfolios formed on within-industry measures are, by construction, highly diversified with respect to industries. In contrast, portfolios formed on market-wide measures are often more concentrated in a few industries.

Although our approach here has been cross-sectional, our results also have implications for asset pricing models in a time-series framework. For example, mimicking portfolios formed by sorting stocks on the basis of their within-industry BE/ME or ME (Cohen and Polk [1998]) should be closer to multifactor minimum variance (Fama [1996]) than portfolios formed using sorts on market-wide factors. The closer a multifactor model's mimicking portfolios are to multifactor minimum variance, the lower the probability of the models' rejection in empirical tests.

For practitioners who employ quantitative stock selection models our results suggest a better way of sorting stocks. For example, portfolios that are long high within-industry BE/ME stocks and short low within-industry BE/ME stocks should have about the same to slightly higher expected return, but less variance than portfolios long high market-wide BE/ME stocks and short low market-wide BE/ME stocks. In fact, the t-statistics in tables 2 through 5 are direct statements about the expected performance of long-short strategies. The risk/return trade-off is consistently superior for strategies based on within-industry variables to those based on variables measured market-wide.

Appendix 1

Fama and French [1997] use four digit SIC codes to assign firms to 48 industries. This appendix lists the range of SIC codes that defines each industry.

Agriculture	0100-0799, 2048-2048
Food Products	2000-2046, 2050-2063, 2070-2079, 2090-2095 2098-2099
Candy and Soda	2064-2068, 2086-2087, 2096-2097
Alcoholic Beverages	2080-2085
Tobacco Products	2100-2199
Recreational Products	0900-0999, 3650-3652, 3732-3732, 3930-3949
Entertainment	7800-7842, 7870-7870, 7900-7999
Printing and Publishing	2700-2749, 2770-2799
Consumer Goods	2047-2047, 2391-2392, 2510-2519, 2590-2599, 2840-2844, 3160-3199, 3229-3231, 3260-3260, 3269-3269, 3630-3639, 3750-3751, 3800-3800, 3860-3879, 3910-3919, 3960-3964, 3970-3970, 3991-3991, 3995-3995
Apparel	2300-2390, 3020-3021, 3100-3111, 3130-3159, 3965-3965
Healthcare	8000-8099
Medical Equipment	3693-3693, 3840-3851
Pharmacetical Products	2830-2836
Chemicals	2800-2829, 2850-2899
Rubber and Plastic Products	3000-3000, 3050-3099
Textiles	2200-2295, 2297-2299, 2393-2395, 2397-2399

Construction Materials	0800-0899, 2400-2439, 2450-2459, 2490-2499, 2950-2952 3200-3219, 3240-3259, 3261-3261, 3264-3264, 3270-3299 3420-3442, 3446-3452, 3490-3499, 3996-3996
Construction	1500-1549, 1600-1699, 1700-1799
Steel Works, Etc.,	3300-3370, 3390-3399
Fabricated Products	3400-3400, 3443-3444, 3460-3479
Machinery .	3510-3536, 3540-3569, 3580-3599
Electrical Equipment	3600-3621, 3623-3629, 3640-3646, 3648-3649, 3660-3660, 3690-3692, 3699-3699
Miscellaneous	3900-3900, 3990-3990, 3999-3999, 9900-9999
Automobiles and Trucks	2296-2296, 2396-2396, 3010-3011, 3537-3537, 3647-3647, 3694-3694, 3700-3716, 3790-3792, 3799-3799
Aircraft	3720-3729
Shipbuilding, Railroad	3730-3731, 3740-3743
Defense	3480-3489, 3760-3769, 3795-3795
Precious Metals	1040-1049, 1101-1101
Non-Metallic Mining	1000-1039, 1060-1099, 1400-1499
Coal	1111-1111, 1200-1299
Petroleum and Natrual Gas	1110-1110, 1310-1390, 2900-2911, 2990-2999
Utilities	4900-4999
Telecommunications	4800-4899
Personal Services	7020-7021, 7030-7039, 7200-7212, 7214-7299, 7395-7395 7500-7500, 7520-7549, 7600-7699, 8100-8199, 8200-8299 8300-8399, 8400-8499, 8600-8699, 8800-8899
Business Services	2750-2759, 3993-3993, 7300-7372, 7374-7394, 7396-7397 7399-7399, 7510-7519, 8700-8799, 8900-8999

Computers	3570-3579, 3680-3689, 3695-3695, 7373-7373
Electronic Equipment	3622-3622, 3661-3679, 3810-3810, 3812-3812
Measuring and Control Equip.	3811-3811, 3820-3832
Business Supplies	2520-2549, 2600-2639, 2670-2699, 2760-2761, 2950-3955
Shipping Containers	2440-2449, 2640-2659, 3210-3221, 3410-3412
Transportation	4000-4099, 4100-4199, 4200-4299, 4400-4499, 4500-4599 4600-4699, 4700-4799
Wholesale	5000-5099, 5100-5199
Retail	5200-5299, 5300-5399, 5400-5499, 5500-5599, 5600-5699 5700-5736, 5900-5999
Restaurants, Hotel and Motel	5800-5813, 5890-5890, 7000-7019, 7040-7049, 7213-7213
Banking	6000-6099, 6100-6199
Insurance	6300-6399, 6400-6411
Real Estate	6500-6553, 6590-6590
Trading	6200-6299, 6700-6799

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Table 1a

Summary Statistics
48 Industries Sorted by Average Monthly Return
7/63-12/98 (426 observations)

Industry	Avg. Return (%/mo.)	Std. Dev. (%/month)	Average # Firms	Avg. Total ME ($ millions)
Tobacco Products	1.63	5.82	6	30,413
Candy and Soda	1.50	5.66	9	42,585
Entertainment	1.48	7.92	31	15,785
Miscellaneous	1.48	10.69	11	1,911
Medical Equipment	1.46	5.78	62	30,744
Healthcare	1.42	8.94	55	19,422
Business Services	1.42	6.35	190	83,728
Restaurants, Hotel and Motel	1.38	6.78	50	22,303
Measuring and Control Equip.	1.37	7.80	54	19,088
Wholesale	1.35	6.40	99	27,423
Pharmaceutical Products	1.35	5.29	72	116,072
Alcoholic Beverages	1.29	5.71	9	8,710
Defense	1.28	6.79	6	5,968
Recreational Products	1.27	7.87	29	10,683
Rubber and Plastic Products	1.25	6.43	23	4,509
Shipbuilding, Railroad	1.25	6.93	6	2,504
Aircraft	1.25	7.01	20	22,984
Retail	1.23	5.82	131	98,044
Insurance	1.22	6.31	45	46,814
Electronic Equipment	1.21	6.63	115	53,829
Printing and Publishing	1.18	5.96	33	26,243
Consumer Goods	1.17	4.96	74	122,878
Coal	1.17	7.94	7	1,927
Food Products	1.16	4.55	51	45,953
Trading	1.15	5.49	177	188,856
Electrical Equipment	1.13	5.96	69	25,117
Agriculture	1.13	7.07	10	1,639
Real Estate	1.10	8.27	22	2,502
Telecommunications	1.09	4.41	44	108,555
Banking	1.09	6.06	77	75,732
Petroleum and Natural Gas	1.09	5.12	129	163,253
Personal Services	1.09	8.28	23	5,755
Non-Metallic Mining	1.08	7.60	17	7,008
Business Supplies	1.07	5.74	34	29,718
Construction Materials	1.06	5.73	93	33,125
Computers	1.06	5.90	83	95,732
Textiles	1.06	6.26	26	3,283
Transportation	1.02	6.43	60	26,290
Apparel	1.02	6.65	46	8,590
Construction	1.01	7.93	29	5,129
Automobiles and Trucks	1.01	5.82	49	61,835
Precious Metals	1.01	10.22	16	4,019
Shipping Containers	0.99	5.12	24	21,857
Chemicals	0.98	5.25	59	64,177
Machinery	0.92	5.86	109	33,722
Utilities	0.86	3.91	141	131,525
Steel Works, Etc.,	0.72	6.19	48	22,931
Fabricated Products	0.65	7.03	12	2,271
Average	1.17	6.51	54	41,315

Table 1b

Summary Statistics
48 Industries Sorted by Book-to-Market Ratio
7/63-12/98 (426 observations)

	BE/ME				C(+)/P				ΔEMP			
Industry	Mean	Median	Min	Max	Mean	Median	Min	Max	Mean	Median	Min	Max
Pharmaceutical Products	0.29	0.24	0.12	0.48	0.06	0.05	0.03	0.10	0.06	0.06	-0.01	0.18
Candy and Soda	0.30	0.23	0.09	0.64	0.07	0.06	0.03	0.17	0.05	0.06	-0.17	0.25
Medical Equipment	0.31	0.31	0.14	0.58	0.06	0.05	0.02	0.11	0.09	0.08	-0.01	0.57
Precious Metals	0.37	0.38	0.19	0.59	0.05	0.05	0.01	0.12	0.08	0.06	-0.12	0.36
Consumer Goods	0.39	0.36	0.16	0.77	0.09	0.08	0.03	0.18	0.05	0.04	-0.05	0.35
Computers	0.40	0.43	0.13	0.83	0.09	0.09	0.04	0.18	0.10	0.07	-0.03	0.63
Measuring and Control Equip.	0.44	0.43	0.22	0.86	0.07	0.07	0.02	0.12	0.09	0.08	-0.02	0.31
Personal Services	0.46	0.40	0.12	0.95	0.07	0.06	0.00	0.16	0.15	0.12	-0.04	0.67
Restaurants, Hotel and Motel	0.48	0.48	0.18	1.20	0.09	0.08	0.03	0.18	0.15	0.11	-0.01	0.68
Business Services	0.50	0.42	0.14	1.47	0.09	0.07	0.03	0.18	0.17	0.16	-0.02	0.64
Printing and Publishing	0.51	0.43	0.23	1.46	0.08	0.08	0.02	0.15	0.07	0.06	-0.07	0.34
Shipping Containers	0.52	0.43	0.27	0.98	0.11	0.10	0.05	0.23	0.03	0.02	-0.11	0.17
Electrical Equipment	0.53	0.48	0.26	1.17	0.09	0.08	0.03	0.17	0.08	0.07	-0.08	0.33
Entertainment	0.54	0.55	0.24	1.33	0.10	0.09	0.03	0.17	0.15	0.12	-0.11	0.89
Retail	0.55	0.48	0.25	1.09	0.09	0.07	0.01	0.19	0.10	0.10	0.00	0.23
Food Products	0.55	0.51	0.22	0.93	0.10	0.09	0.04	0.19	0.05	0.04	-0.03	0.19
Tobacco Products	0.56	0.59	0.22	0.82	0.11	0.10	0.05	0.17	0.07	0.05	-0.13	0.46
Recreational Products	0.57	0.55	0.18	1.47	0.10	0.09	0.03	0.20	0.10	0.10	-0.14	0.39
Electronic Equipment	0.61	0.62	0.26	1.55	0.12	0.11	0.05	0.26	0.08	0.07	-0.08	0.26
Chemicals	0.66	0.63	0.29	1.21	0.14	0.12	0.05	0.30	0.01	0.01	-0.08	0.11
Wholesale	0.68	0.56	0.35	1.42	0.10	0.08	0.05	0.21	0.20	0.12	0.03	0.91
Alcoholic Beverages	0.68	0.59	0.31	1.32	0.11	0.10	0.03	0.20	0.07	0.02	-0.37	0.77
Construction Materials	0.70	0.63	0.28	1.47	0.12	0.11	0.06	0.24	0.06	0.06	-0.09	0.21
Miscellaneous	0.71	0.71	0.20	1.52	0.11	0.09	0.03	0.25	0.18	0.12	-0.09	1.46
Machinery	0.72	0.72	0.30	1.30	0.12	0.11	0.06	0.25	0.06	0.06	-0.16	0.21
Agriculture	0.75	0.56	0.30	2.64	0.09	0.09	0.03	0.25	0.10	0.07	-0.16	0.46
Coal	0.77	0.76	0.38	1.31	0.14	0.14	0.01	0.25	0.04	0.03	-0.15	0.56
Rubber and Plastic Products	0.77	0.67	0.32	1.69	0.12	0.10	0.05	0.29	0.10	0.07	-0.09	0.85
Apparel	0.78	0.60	0.39	3.01	0.12	0.09	0.04	0.31	0.09	0.08	-0.04	0.37
Business Supplies	0.79	0.73	0.44	1.26	0.14	0.12	0.04	0.29	0.02	0.02	-0.06	0.13
Construction	0.80	0.71	0.29	1.74	0.12	0.10	0.04	0.25	0.14	0.13	-0.08	0.54
Non-Metallic Mining	0.80	0.75	0.41	1.63	0.11	0.10	0.03	0.29	0.08	0.06	-0.21	0.39
Petroleum and Natural Gas	0.81	0.73	0.40	1.38	0.17	0.15	0.10	0.35	0.02	0.02	-0.21	0.13
Healthcare	0.82	0.46	0.30	4.99	0.08	0.06	0.00	0.35	0.27	0.20	0.03	1.11
Telecommunications	0.84	0.80	0.30	1.67	0.16	0.14	0.05	0.30	0.04	0.03	-0.03	0.28
Aircraft	0.85	0.75	0.27	2.22	0.17	0.16	0.06	0.34	0.04	0.03	-0.16	0.50
Trading	0.85	0.85	0.33	1.75	0.11	0.11	0.02	0.21	0.12	0.06	-0.06	0.82
Fabricated Products	0.86	0.80	0.42	2.27	0.12	0.11	0.04	0.23	0.07	0.05	-0.18	0.70
Banking	0.88	0.78	0.35	1.56	0.08	0.08	0.03	0.17	0.09	0.07	-0.04	0.63
Insurance	0.90	0.87	0.17	1.30	0.07	0.08	0.00	0.17	0.07	0.06	-0.04	0.36
Real Estate	0.91	0.70	0.25	3.72	0.09	0.07	0.02	0.30	0.14	0.10	-0.22	1.15
Defense	0.92	0.82	0.29	2.13	0.18	0.17	0.03	0.35	0.00	-0.01	-0.26	0.27
Shipbuilding, Railroad	0.97	0.89	0.36	1.63	0.16	0.13	0.05	0.41	0.02	0.03	-0.43	0.26
Automobiles and Trucks	0.99	0.95	0.40	1.94	0.24	0.24	0.10	0.46	0.02	0.03	-0.12	0.11
Utilities	1.03	1.01	0.44	1.85	0.17	0.16	0.08	0.29	0.03	0.02	-0.01	0.31
Transportation	1.03	0.93	0.49	2.24	0.18	0.17	0.08	0.34	0.08	0.07	-0.03	0.50
Steel Works, Etc.,	1.05	0.99	0.58	1.80	0.16	0.13	0.05	0.41	0.02	0.02	-0.13	0.15
Textiles	1.18	1.04	0.51	3.27	0.16	0.13	0.08	0.32	0.06	0.05	-0.07	0.42
Average:	0.70	0.63	0.29	1.59	0.11	0.10	0.04	0.24	0.08	0.07	-0.10	0.47

Each month, each industry ratio equals the value-weighted average of the ratios of the industry's constituents. In some of the early months of our sample, a few industries did not have any firms with the necessary accounting data. All of the calculations in table 1 are based on the maximum length time-series average of the number of firms in each industry. "Average Return (%/mo.)" is the time-series average of the value-weighted returns for each industry. "Average # firms" is the time-series average of the number of firms in each industry. "Average Total ME (millions)" is the time-series average of the total market capitalization (in millions) of each industry. Beginning with the NYSE/AMEX/Nasdaq universe, we omit firms with negative BE/MEs or missing returns and we only include firms that have been on COMPUSTAT for at least two years. In calculating BE/ME and C(+)/P, BE C(+), and ME are updated annually. Each July we form BE/ME and C(+)/P from each firm's prior end of December ME and their prior year's BE and C(+). ΔEMP is formed analogously, but without any ME adjustment. Thus, there is at least a six month lag between the actual date of the information and the date we use the information. This December to July lag insures that accounting data would actually be available at the time portfolios are formed. In contrast, ME is based on its value as of the end of the previous month. As in Fama and French (1992), the smallest and largest 0.5% of the observations on each variable are set equal to the next smallest or largest values of the variables (the 0.005 and 0.995 fractiles).

Table 2

Single Variable Monthly Cross-Sectional Regressions
Average Slopes (t-statistics)
7/63 – 12/98 (426 observations)

Market-wide regression equation: $R_{it} = \gamma_{At} + \gamma_{Bt}X_{it} + \varepsilon_{it}$ (1)

Industry regression equation: $R_{it} = \gamma_{ot} + \gamma_{1t}X_{Iit} + \gamma_{2t}(X_{it} - X_{Iit})$ (2)

Alternate industry regression equation: $R_{it} = \gamma_{ot} + (\gamma_{1t} - \gamma_{2t})X_{Iit} + \gamma_{2t}X_{it}$ (3)

		Market-wide	Across-Industry	Within-Industry	C/P Dummy
log(ME)	(1)	-0.18 (-3.68)			
	(2)		-0.04 (-0.45)	-0.20 (-4.28)	
	(3)	-0.20 (-4.28)	0.16 (2.43)		
log(BE/ME)	(1)	0.49(6.98)			
	(2)		0.19 (1.14)	0.54 (9.27)	
	(3)	0.54 (9.27)	-0.35 (-2.54)		
C(+)/P	(1)	2.29(4.59)			0.32 (2.46)
	(2)		0.69 (0.52)	2.38 (5.66)	0.32 (2.43)
	(3)	2.38 (5.66)	-1.69 (-1.47)		0.32 (2.43)
ΔEMP	(1)	-0.58(-4.94)			
	(2)		0.98 (1.49)	-0.67 (-6.86)	
	(3)	-0.67 (-6.86)	1.65 (2.67)		
PAST(13,60)	(1)	-0.15(-3.61)			
	(2)		-0.16 (-1.59)	-0.15 (-4.18)	
	(3)	-0.15 (-4.18)	-0.01 (-0.14)		
PAST(2,12)	(1)	0.06(4.15)			
	(2)		0.30 (6.28)	0.04 (3.40)	
	(3)	0.04 (3.40)	0.26 (6.29)		
PAST(1,1)	(1)	-0.05(-11.69)			
	(2)		0.19 (10.87)	-0.07 (-16.39)	
	(3)	-0.07 (-16.39)	0.26 (16.45)		

X_{it} refers to the market-wide measure of variable X for firm i at time t while X_{Iit} refers to the industry average value. Each month, each industry ratio equals the average of the ratios of the industry's constituents. In some early months of our sample, a few industries did not have any firms with the necessary accounting data. We also require each industry to have at least three constituents with the necessary data. If this requirement is not satisfied, the industry is omitted from the regression. We omit firms with negative BE/MEs or missing returns and we only include firms that have been on COMPUSTAT for at least two years. In calculating BE/ME and C(+)/P, BE C(+), and ME are updated annually. Each July we form BE/ME and C(+)/P from each firm's prior end of December ME and their prior year's BE and C(+). ΔEMP is formed analogously, but without any adjustment. Thus, there is at least a six month lag between the actual date of the information and the date we use the information. this December to July lag insures that accounting data would actually be available at the time portfolios are formed. In contrast, ME is based on its value as of the end of the previous month. As in Fama and French (1992), the smallest and largest 0.5% of the observations on each variable are set equal to the next smallest or largest values of the variables (the 0.005 and 0.995 fractiles).

Table 3

Quintile Spreads
Average Returns, Standard Deviations, t-statistics, and Percent of Months Positive
8/63 – 12/98 (425 observations)

	Equal-Weight Portfolios				Value-Weight Portfolios			
ME	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	-0.95	5.35	-3.68	45.07	-0.51	5.51	-1.93	49.77
Within-Industry	-0.94	4.76	-4.07	43.66	-0.44	4.39	-2.06	49.53
Across-Industry	-0.07	3.38	-0.43	50.23	-0.19	3.36	-1.19	49.77
BE/ME	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	1.11	3.36	6.71	62.91	0.44	3.68	2.48	53.52
Within-Industry	1.08	2.50	8.80	66.20	0.45	2.93	3.14	57.28
Across-Industry	0.21	3.46	1.24	49.06	0.01	3.26	0.09	49.77
C(+)/P	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	0.34	2.74	2.54	55.16	0.26	3.86	1.40	53.76
Within-Industry	0.44	1.96	4.58	58.69	0.29	2.59	2.35	53.29
Across-Industry	-0.02	2.82	-0.15	50.00	0.00	3.28	0.00	48.83
ΔEMP	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	-0.49	2.02	-4.98	39.44	-0.11	2.80	-0.79	49.77
Within-Industry	-0.53	1.62	-6.72	32.16	-0.17	2.15	-1.66	47.18
Across-Industry	0.11	3.03	0.73	48.33	-0.02	3.13	-0.16	49.06
PAST(13,60)	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	-0.73	3.80	-3.65	36.62	-0.25	4.25	-1.14	42.02
Within-Industry	-0.66	3.14	-4.05	34.51	-0.15	3.40	-0.86	41.78
Across-Industry	-0.30	3.11	-1.88	37.79	-0.20	3.44	-1.09	43.90
PAST(2,12)	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	0.98	3.97	5.04	64.79	1.22	5.09	4.88	60.56
Within-Industry	0.69	3.12	4.48	61.03	1.11	3.69	6.11	66.43
Across-Industry	0.94	3.54	5.42	62.44	0.35	3.68	1.92	55.40
PAST(1,1)	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +	Q5-Q1 (%/mo)	Std. Dev.	t-statistic	% Months +
Market-Wide	-1.88	3.58	-10.82	25.82	-0.34	3.99	-1.76	49.30
Within-Industry	-2.41	3.15	-15.78	14.32	-1.29	3.25	-8.16	31.22
Across-Industry	1.59	3.16	10.33	72.54	0.97	3.36	5.99	64.08

Table 4

Value-Weighted Market-Wide, Within-Industry, and (Within-Industry-Market-Wide) Quintile Spreads
Within-Industry and Market-Wide Arbitrage Portfolios Levered to Equal (5%) σ
Average Returns, t-statistics, and Percent of Months Positive
7/63 – 12/98 (426 observations)

ME	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	-0.47	-1.93	49.77
Within-Industry	-0.50	-2.06	49.53
Equal σ^2 Diff.	-0.03	-0.54	50.00

BE/ME	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	0.60	2.48	53.52
Within-Industry	0.76	3.14	57.28
Equal σ^2 Diff.	0.16	0.94	50.70

C(+)/P	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	0.34	1.40	53.76
Within-Industry	0.57	2.35	53.29
Equal σ^2 Diff.	0.23	1.42	49.53

ΔEMP	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	-0.19	-0.79	49.77
Within-Industry	-0.40	-1.66	47.18
Equal σ^2 Diff.	-0.21	-1.08	49.77

PAST(13,60)	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	-0.30	-1.15	42.02
Within-Industry	-0.23	-0.86	41.78
Equal σ^2 Diff.	0.07	0.59	42.72

PAST(2,12)	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	1.20	4.88	60.56
Within-Industry	1.50	6.11	66.43
Equal σ^2 Diff.	0.30	2.24	46.01

PAST(1,1)	Q5-Q1 (%/mo)	t-statistic	% Months +
Market-Wide	-0.43	-1.76	49.30
Within-Industry	-1.98	-8.16	31.22
Equal σ^2 Diff.	-1.55	-11.12	35.21

Each month, each industry ratio equals the value-weighted average of the ratios of the industry's constituents. In some of the early months of our sample, a few industries did not have any firms with the necessary accounting data. We also require each industry to have at least three constituents with the necessary data. If this requirement is not satisfied the industry is omitted. We omit firms with negative BE/MEs or missing returns an we only include firms that have been on COMPUSTAT for at least two years. In calculating BE/ME and C(+)/P, BE, C(+), and ME are updated annually. Every July, we form BE/ME and C(+)/P from each firm's prior end of December ME and their prior year's BE and C(+). ΔEMP is formed analogously, but without any ME adjustment. Thus, there is at least a six month lag between the actual data of the information and the date we use the information. This December to July lag insures that the accounting data would actually be available at the time portfolios are formed. In contrast, ME and each of our past return variables are based on the values as of the end of the previous month. for each variable, we form 2 sets of quintile portfolios by sorting stocks on their (1) market-wide and (2) Within- industry characteristics. We then form a zero-investment portfolio returns by subtracting the return on quintile 1 (Q1) from the returns on quintile 5 (Q5). We scale each zero investment portfolio to have a 5% monthly standard deviation. The Equal σ^2 Diff portfolio subtracts the returns on the market –wide zero investment portfolio form the returns on the Within-industry zero investment portfolio.

Table 5

Value-Weighted Quintile Spreads with PAST(1,1)
Average Returns, t-statistics, and Percent of Months Positive
7/63 – 12/98 (426 observations)

PAST(1,1) and Volume

		Market-Wide			Across-Industry			Within-Industry		
Volume Decile	Avg. Share Volume per firm (thousands)	Q5-Q1 % per month	t-stat.	% months +	Q5-Q1 % per month	t-stat.	% months +	Q5-Q1 % per month	t-stat.	% months +
Lowest	49	-2.51	-13.21	23.53	1.37	10.29	69.18	-2.98	-16.35	16.94
2	186	-2.62	-12.03	26.82	1.78	10.53	70.12	-3.11	-15.04	21.18
3	327	-1.92	-8.08	35.53	1.56	8.16	65.18	-2.45	-11.50	29.18
4	515	-1.77	-7.92	36.47	1.59	8.21	62.82	-2.24	-10.38	31.06
5	777	-1.44	-5.54	41.41	1.42	6.77	63.06	-1.88	-7.82	35.06
6	1133	-1.14	-4.64	42.59	1.28	5.87	62.12	-1.63	-6.97	35.06
7	1657	-0.92	-3.77	41.65	1.46	6.91	64.47	-1.37	-6.07	38.59
8	2490	-0.44	-1.68	49.41	1.52	6.54	62.82	-1.06	-4.36	43.53
9	4138	-0.35	-1.38	49.41	1.00	4.27	58.12	-0.72	-3.31	44.94
Highest	11743	0.06	0.25	52.00	1.02	3.96	61.41	-0.40	-1.85	44.71

PAST(1,1) and ME

		Market-Wide			Across-Industry			Within-Industry		
Size Decile	Avg. ME per firm ($ millions)	Q5-Q1 % per month	t-stat.	% months +	Q5-Q1 % per month	t-stat.	% months +	Q5-Q1 % per month	t-stat.	% months +
Lowest	24	-3.34	-16.34	13.88	1.45	10.01	70.82	-3.60	-18.38	13.41
2	93	-1.17	-5.91	36.94	1.31	8.00	66.12	-1.64	-8.85	31.53
3	160	-0.82	-4.32	44.71	1.61	9.30	68.71	-1.46	-7.94	35.06
4	242	-0.89	-4.68	44.24	1.15	6.34	62.59	-1.42	-8.19	34.59
5	366	-1.08	-5.80	40.24	1.16	6.12	63.06	-1.46	-9.37	32.00
6	550	-1.01	-5.59	38.12	1.24	6.58	63.76	-1.66	-9.80	29.88
7	852	-0.82	-4.45	39.29	1.38	7.20	64.00	-1.41	-8.72	32.94
8	1406	-1.07	-5.77	40.94	0.89	4.50	57.65	-1.55	-9.64	31.53
9	2527	-0.82	-4.83	41.18	0.67	3.43	59.53	-1.36	-10.02	30.35
Highest	10693	-0.27	-1.55	45.88	0.71	3.68	57.18	-0.86	-7.27	33.65

At the end of each month from June 1963-November 1998, all NYSE, AMEX and NASDAQ (beginning in 1973) are sorted into deciles based on their share trading volume over the month(bottom panel) or their ME (top panel). We use NYSE breakpoints to define the volume and ME deciles. NASDAQ volume is adjusted for Interdealer trades as discussed in the text. Within each decile, stocks are then sorted in quintiles based on their market-wide, within-industry, and across-industry return over the month. We value-weight the 50 portfolios that comprise the volume or ME decile/PAST(1,1) quintile intersections, measure the return to each portfolio over the following month, and then re-sort.

Table 6

Momentum Profits for Individual Equities, Industry Portfolios, and Within-Industry Portfolios
Formed on Six Month Ranking Period and Held for Six Months
(t-statistics in parentheses)
7/63-12/98 (426 observations)

Ranking Period	Market-wide	Across-Industry Portfolios		Within-Industry Portfolios	
		FF Industries	MG Industries	FF Industries	MG Industries
PAST(1,6)	0.0043	0.0065	0.0031	0.0043	0.0042
	(2.46)	(3.59)	(1.85)	(3.56)	(3.15)
PAST(2,7)	0.0068	0.0078	0.0047	0.0061	0.0059
	(4.02)	(4.38)	(2.79)	(5.41)	(4.75)

Average monthly momentum profits for portfolios of winners minus losers for July 1963 through December of 1998 (n=413). An average return of 0.0043 is 43 basis points per month. Winners and losers are defined based on total return during the ranking period. Each ranking period is 6 months in length and each portfolio is held for 6 months. PAST(1,6) is the 6 month period immediately prior to portfolio formation. PAST(2,7) is the 6 month period beginning 1 month prior to portfolio formation. Market-wide refers to the ranking of all stocks by total return during the ranking period. Winners are defined as the top 30% and losers the bottom 30%. Across-Industry Portfolios are formed based on total return to value-weighted industry portfolios during the ranking period. Winning industries are the top 15% and losers the bottom 15% of industries during the ranking period. The average monthly profit from a strategy of buying an equally-weighted portfolio of the winning value-weighted industry portfolios and shorting the losing industries and holding for six months is reported. FF industries refer to the 48 industries defined in appendix 1. MG industries refer to the 20 industries defined in Moskowitz and Grinblatt (1999), table 1.

Within-Industry Portfolios refers to the ranking of all stocks by difference in return from their value-weighted industry average. Winners are defined as the top 30% of stocks during the ranking period and losers the bottom 30%. The average monthly profit from a strategy of buying a value-weighted portfolio of winners and shorting a value-weighted portfolio of losers and holding the position for 6 months is reported.

Table 7

Momentum Profits for Value-Weighted Portfolios Formed by Across-Industry Momentum and Within-Industry Momentum.
Formed on Six Month Ranking Period and Held for Six Months
(t-statistics in parentheses)
[Average number of firm in brackets]
7/63-12/98 (426 observations)

		Within-Industry Portfolios (A) Loser	(B) Middle	(C) Winner
Across-Industry Portfolios	(1) Loser	0.0038 (1.15) [73]	0.0087 (3.37) [143]	0.0115 (4.29) [122]
	(2) Middle	0.0069 (2.58) [665]	0.0097 (4.63) [920]	0.0135 (5.39) [665]
	(3) Winner	0.0117 (4.27) [138]	0.0147 (5.71) [118]	0.0176 (5.78) [90]
	Win/Win - Lose/Lose		0.0138 (4.73)	

Average monthly holding period returns for portfolios formed on across-industry and within-industry momentum for July 1963 through December of 1998 (n=413). An average return of 0.0138 is 1.38% per month. Winners and losers are defined based on total return during the ranking period. Each ranking period is 6 months beginning in month t-2 and extending to month t-7, skipping a month between ranking and portfolio formation. Across-Industry Portfolios are formed based on total return to value-weighted industry portfolios during the ranking period with the industries being those defined in appendix 1. Within-Industry winners and losers are formed based on a ranking of all stock by difference in return from their value-weighted industry average. Winners are defined as the top 30% of stocks during the ranking period and losers the bottom 30%. Each cell is the average monthly return of a value weighted portfolio formed by the intersection of the two ranking criteria. For example, cell 3C is the average monthly return to a value-weighted portfolio formed from all stocks in the top 30% of a ranking of total return over months t-2 through t-7 less the value-weighted industry average who are also in one of the 15% top performing industries over the same period and holding the resulting portfolio for six months.

The Win/Win – Lose/Lose is the average monthly return to a zero-investment strategy of long those stocks in cell 3C and short those stocks in cell 1A. The average number of firms in each cell is reported in brackets.

Table 8

Momentum Profits for Value-Weighted Portfolios Formed by Across-Industry Momentum and Within-Industry Momentum.
Large Stocks Only
Formed on Six Month Ranking Period and Held for Six Months
(t-statistics in parentheses)
[Average number of firm in brackets]
7/63-12/98 (426 observations)

		Within-Industry Portfolios		
		(A) Loser	(B) Middle	(C) Winner
Across-Industry Portfolios	(1) Loser	0.0055 (1.77) [26]	0.0092 (3.63) [45]	0.0107 (4.00) [35]
	(2) Middle	0.0085 (3.49) [204]	0.0097 (4.70) [276]	0.0131 (5.28) [196]
	(3) Winner	0.0122 (4.60) [35]	0.0146 (5.68) [34]	0.0178 (5.74) [27]
	Win/Win - Lose/Lose		0.0123 (4.36)	

Each month, all firms below the median market capitalization of all NYSE/AMEX stocks in that industry in that month are dropped from the sample (the sample includes Nasdaq stocks, however). This results in a drop of approximately 70% of the firm observations in the sample. These small firms are used to calculate value-weighted industry averages but are not used in calculating the 30% and 70% within-industry breakpoints nor are they included in the value-weighted portfolios whose average monthly returns are reported in the table.

Average monthly holding period returns for portfolios formed on across-industry and within-industry momentum for July 1963 through December of 1998 (n=413). A return of 0.0123 is 1.23% per month. Winners and losers are defined based on total return during the ranking period. Each ranking period is 6 months beginning in month t-2 and extending to month t-7, skipping a month between ranking and portfolio formation. Across-Industry Portfolios are formed based on total return to value-weighted industry portfolios during the ranking period with the industries being those defined in appendix 1. Within-Industry winners and losers are formed based on a ranking of all stock by difference in return from their value-weighted industry average. Winners are defined as the top 30% of stocks during the ranking period and losers the bottom 30%. Each cell is the average monthly return of a value weighted portfolio formed by the intersection of the two ranking criteria. For example, cell 3C is the average monthly return to a value-weighted portfolio formed from all stocks in the top 30% of a ranking of total return over months t-2 through t-7 less the value-weighted industry average who are also in one of the 15% top performing industries over the same period and holding the resulting portfolio for six months.

The Win/Win – Lose/Lose is the average monthly return to a zero-investment strategy of long those stocks in cell 3C and short those stocks in cell 1A. The average number of firms in each cell is reported in brackets.