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"The Cross Section of Expected Returns and its Relation to Past Returns: New Evidence"

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Abstract

This paper parsimoniously characterizes how past returns affect the cross-section of expected returns. Using Fama-MacBeth regressions, it shows that the momentum and reversals associated with past returns over various horizons are strongly affected by a turn-of-the-year seasonal that differs for winners and losers, depending on both the tax environment and the month of the year, and differs by exchange listing. The analysis also uncovers a consistent winners effect – high fractions of positive return months tend to increase expected returns. Out-of-sample evidence suggests that the documented relation between past returns and expected returns cannot entirely be due to data snooping biases.

Introduction

Within the last fifteen years, researchers have discovered that past returns contain information about expected returns. Inferring what it is about past returns that drives the cross-section of ex-ante expected returns has been a particularly difficult exercise. One reason for this is that return volatility is so large, making it critical that a long historical time series be used to generate reliable inferences. In addition, there are pronounced seasonalities in the data, such as the January effect, and structural changes in the economy that appear to alter the underlying parameters of the return generating process.

Robust inference on this topic is also complicated by what some researchers (e.g., see Lo and MacKinlay (1990)) have termed "data snooping." Empirical researchers have largely focused on the same datasets of stock returns over the past two decades. It may be that the ex-post fit of the best past return horizons to the data is not a reliable way to generate inferences that will work ex-ante. A case in point is the approximately 6% (value-weighted) and 12% equal-weighted portfolio return generated by buying past 6-month winners, shorting past 6-month losers, and holding for 6 months. The profit from this strategy, according to Moskowitz and Grinblatt (1999), largely disappears once book-to-market, size, and industry are controlled for.

This paper presents new evidence on the relation between past returns and the cross-section of expected returns. It uses Fama-MacBeth regressions and a stock ranking system derived from these regressions to form in- and out-of-sample portfolio strategies that parsimoniously characterize the relation between past returns and expected returns. The analysis here finds that the past returns of stocks affect their expected returns in a particularly complex way. The literature has shown that both short-term (less than 1 month) past returns and long-term (3-5 year) past returns are inversely related to future average returns, while intermediate horizon past returns (3-12 months) are positively related to future average returns.[1] However, decomposing these various horizons into past winner and loser return components, while controlling for other determinants of expected returns, shows that this relationship is more complex. In particular, the winner-loser components have asymmetric effects on returns that vary with the month of the year and the tax environment in a sensible way. In addition, it is not only the past return, per se, but also the consistency of the

[1]The classic papers that present evidence on the cross-section of expected returns of short-term reversals, intermediate term momentum, and long-term reversals are Jegadeesh (1990), Jegadeesh and Titman (1993), and DeBondt and Thaler (1985), respectively.

past return that matters. Particularly for NASDAQ stocks, consistent past winners have higher expected returns than winners with performance arising from a few extraordinary months.

Our approach analyzes the simultaneous effect of all of the relevant past return variables on the future returns of hedged positions in individual stocks. Such hedged positions have their book-to-market, size, and industry return components eliminated and are beta neutral as well. We believe that this hedged stock approach can better assess the marginal impact of each past return variable on the cross-section of expected returns. For example, studies of long/short strategies based on past return patterns typically cannot determine whether the short or the long side drives the abnormally large profit. Under the null hypothesis of no effect from past returns, our hedged portfolios, both long and short, should have expected returns of zero. This is because they are zero cost portfolios that control for known determinants of return premia. Hence, non-zero regression coefficients on positive (negative) past return variables indicate that it is the long (short) side of an investment that is profitable. Taking out book-to-market, size, and industry also lowers volatility, which generates more powerful tests of whether return premia depend on past returns.

Our analysis is careful to differentiate return processes in different months, separating January, as well as December, from the rest of the year. We also attempt to differentiate return-generating processes that may vary with structural changes in the economy – in particular those generated by changes in the tax code. In contrast to earlier work, we find strong evidence of December effects from 1- and 3-year past returns that are generally of opposite sign from the effects of past returns in January. Both findings are consistent with tax loss selling at the end of the year. We suspect that tax avoidance behavior is driving many of these results because the seasonal differences in the characterization of the cross-section of expected returns mirror our analysis of how tax code changes affect the characterization of the cross-section of expected returns. For instance, when effective capital gains tax rates are expected to decrease, investors have an incentive to accelerate the realization of their losses. This makes momentum strategies stronger due to increased selling pressure on losing stocks, but makes contrarian strategies relatively less profitable. We find evidence consistent with both of these predictions. Similarly, when expected tax code changes favor deferral of losses, the opposite occurs: Contrarian strategies become relatively more profitable and the profits from momentum strategies decline.

We also attempt to control for market microstructure effects and perform experiments that analyze the biases imparted by data snooping. In much of our analysis, for example, we throw out the performance contributed by returns in the prior month. These prior-month returns could affect future returns because of bid-ask bounce or related liquidity effects. We conclude that the impact of market microstructure contamination on the profitability of our past returns portfolio strategies is minimal – on the order of 17 basis points per month. Moreover, we find that data snooping biases cannot account for most of the profitability of our past returns portfolio strategy.

Taking these results together, we find that the influence of past returns on expected returns is quite complex – exhibiting strong seasonal patterns, generating asymmetric effects among past winners and losers, depending heavily on the tax environment, and modified by consistency in the sign of the historical monthly return series. Despite this complexity, we offer a simple scoring system using Fama-MacBeth regressions that parsimoniously quantifies the economic magnitude of these effects and performs remarkably well out of sample and with potential market microstructure contamination removed.

The rest of the paper is organized as follows. Section I reviews the literature on the cross-section of expected returns and highlights some of the theories offered for the curious autocorrelation and seasonal patterns in returns. Section II briefly describes the data used in our empirical analysis. Section III reports the coefficients and test statistics for Fama-MacBeth regressions that describe how past returns affect the cross-section of expected returns. In addition to analyzing how exchange listing affects these coefficients, this section analyzes how the month of the year and changes in the tax code affect the regression coefficients. Section IV translates the Fama-MacBeth scoring system into a stock ranking, and analyzes how the best- and worst-scored stocks perform both in sample and out of sample. This section also focuses on which sectors of the stock market have expected returns that are most affected by past returns. These sectors are based on firm size, book-to-market ratios, trading volume, and institutional ownership. Finally, Section V summarizes and concludes the paper.

I. Previous Literature

Over the past 25 years, an important line of empirical research in finance has attempted to parsimoniously characterize the cross-section of expected stock returns. In the early 1970s, beta, motivated by the CAPM, was initially found to be a promising stock attribute. This promise was short lived as in short succession, skewness (Kraus and Litzenberger (1976)), dividend yield

(Litzenberger and Ramaswamy (1980)), P/E ratios (Basu (1983)), and, most importantly, firm size (Banz (1981)), which subsumed many of these other effects, began to be viewed as important additional determinants of average stock returns.

The empirical importance of additional factors beyond market beta was recognized by Roll and Ross (1980), Chen, Roll, and Ross (1986), and Chan, Chen, and Hsieh (1985). To date, these APT-inspired approaches, despite their theoretical appeal, have not been able to fully capture the cross-section of expected returns, particularly the component of returns that is related to size. In the 1980s, Huberman, Kandel, and Karolyi (1987), recognizing that firms of similar size tended to move together, proposed size factors as a method of explaining the cross-section of expected returns. This approach was elaborated on in a series of mutual fund papers by Grinblatt and Titman (1988, 1989, 1994) who suggested that an 8-factor model which includes the Huberman-Kandel-Karolyi factors, as well as dividend yield and past return factors, might capture the cross-section of expected stock returns.

A more elegant model, developed in a series of papers in the early 1990s by Fama and French (1992, 1993, 1996), suggested that many of the expected return anomalies in finance could be captured by sensitivity to just three factors: the market, a size factor generated by a long position in a small cap portfolio and a short position in a large cap portfolio, and a book-to-market factor generated by a long position in a portfolio of value (high BE/ME) stocks and a short position in a portfolio of growth (low BE/ME) stocks. Variations of this approach exist for explaining expected returns, such as the Lakonishok, Shleifer, and Vishny (1994) glamour/value classification, and the Daniel and Titman (1997) size and book-to-market attribute classification scheme. Some of these approaches exclude beta, arguing that it has no explanatory power once size is controlled for. While there is some debate about the importance of beta,[2] size and book-to-market have emerged as the dominant contributors to expected returns.

A. Past Returns and the Cross-Section of Expected Returns

This two-attribute view of the cross-section of expected returns, while appealing in its simplicity, is complicated by the existence of profitable trading strategies based on past returns, which is

[2]Jagannathan and Wang (1996) argue that human capital enhances beta as a critical determinant of expected returns.

the focus of our paper.[3] DeBondt and Thaler (1985) document that expected returns are low for stocks with high returns over the past several years and vice versa. Jegadeesh (1990) finds that the pattern over other horizons is more complex, with strong return reversals over the past month,[4] and persistence in returns going out to a year. Following this line of inquiry, Jegadeesh and Titman (1993) demonstrate that momentum strategies – buying winners and selling losers using 3- to 12-month past returns to form portfolios – can generate an astounding 12% per year for a zero-cost zero-beta strategy.

Several papers have attempted to incorporate past returns into a model of the cross-section of expected returns. Carhart (1997), for example, supplements the Fama-French 3-factor model with a fourth factor portfolio, constructed from a long position in a portfolio of high past 12-month return stocks and a short position in low past 12-month return stocks. Daniel, Grinblatt, Titman, and Wermers (1997) analogously extend the Daniel and Titman (1997) model to incorporate 12-month past returns as an attribute for explaining average returns. More recently, Moskowitz and Grinblatt (1999) argue that industry momentum should replace individual stock momentum as an expected return attribute at all but the 12-month past return horizon and that 1-month industry momentum is a separate variable that can generate almost a 20% per year abnormal return on a long-short strategy.

B. Seasonalities in Stock Return Premia, Window Dressing, and Capital Gains Taxes

The two-attribute view of the cross-section of expected returns is also tarnished by the seasonality in stock returns. For example, the enormous 5-7% return premium for small firms in January (most of it in the first few trading days of the year), accounts for the bulk of the size effect, presenting a challenge to those seeking to parsimoniously capture the cross-section of expected returns.[5]

A variety of explanations have been offered for the abnormally large returns of small firms in

[3]Anomalous strong autocorrelation in stock returns at various horizons has been documented by (among others) DeBondt and Thaler (1985, 1987), Lo and MacKinlay (1988), Conrad and Kaul (1988, 1989), Lehman (1990), Jegadeesh (1990), Jegadeesh and Titman (1993), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Hong, Lim, and Stein (1999), Grundy and Martin (1999), and Lee and Swaminathan (1999).

[4]Some of this may be spuriously due to liquidity effects. For example, see Kaul and Nimalendran (1990), Asness (1995), Lo and MacKinlay (1988), Boudoukh, Richardson, and Whitelaw (1994), and Jegadeesh and Titman (1995a,b).

[5]January effects, which are related to both size and past returns, have been documented and analyzed by, among others, Dyl (1977), Roll (1983), Keim (1983, 1989), Reinganum (1983), Berges, McConnell, and Schlarbaum (1984), Chan (1986), Lakonishok and Smidt (1986), Reinganum and Shapiro (1987), Dyl and Maberly (1992), and Poterba and Weisbenner (1998).

the first trading days of January. Lakonishok, Shleifer, Thaler, and Vishny (1991) contend that "window dressing" by institutional investors creates price pressure that produces these returns. Specifically, institutional money managers may sell their losing investments just prior to year-end when they must disclose their portfolio holdings. This selling pressure will cause the share prices of poorly performing firms over the prior year to decline further in December, and then subsequently rebound in January. Since smaller firms are more volatile and less liquid, this effect is more pronounced among small stocks. However, to date, such December selling pressure does not appear to have a great effect on December stock returns. Moreover, the yearly reporting period for most mutual funds, more often than not, is asynchronous with the calendar year cycle.

Another explanation for the year-end effect is the tax-loss selling hypothesis. Here, rather than institutional investors, it is primarily individual investors faced with capital gains taxation who exert price pressure on losing stocks at the end of the year. Because realized capital losses can be used to reduce taxes on realized capital gains or other income in the calendar year, taxable investors have incentives to realize such losses before year-end.[6] Again, this selling pressure will drive down the share prices of losing stocks in December and generate a rebound in January as the selling pressure is alleviated.

Numerous studies have analyzed the tax-loss selling hypothesis, primarily focusing on stock returns in January. The most comprehensive to date may be Poterba and Weisbenner (1998). Their paper analyzes how returns in the first few trading days of January over the 1963 to 1982 time period vary with changes in the holding period definition of short and long-term gains, as well as changes in the dollar limit on losses used to offset adjusted gross income. Our study looks at changes in the maximum capital gains tax rate and analyzes both December and January returns in the 1966 to 1995 period. It presents what we believe is the first documenation of a significant December effect. Also, unlike Poterba and Weisbenner (1998), we analyze how 1-year momentum, 3-year reversals, year-end return effects, asymmetric winner/loser effects, and tax regimes interact with one another in determining the cross-section of expected returns in order to better understand how tax-loss trading affects stock prices.

Seasonal patterns in the profitability of trading strategies based on past returns have also

[6] Of course, as Constantinides (1984) shows, there should be no increase in tax-loss selling at the end of the year when short and long-term gains are treated equally and there are no transactions costs. However, it is common folk wisdom that investors pay attention to the tax implications of their portfolios at the end of the year. This has been documented for Finnish investors by Grinblatt and Keloharju (1999).

been documented by Jegadeesh and Titman (1993). Their paper identifies positive profits for momentum strategies in every month except January, for which they document significant negative profits. Jegadeesh and Titman (1993) also find stronger momentum profits in April, November, and December. They suggest that this may be due to tax-motivated trades. However, their seasonality results focus on a 6-month trading strategy. After hedging out the effects of industry, size, and book-to-market, the only momentum strategy which generates significant profits is at a ranking horizon of 1 year, which we address in this paper. In addition, Jegadeesh and Titman (1993) do not separate out the seasonal effects on winners and losers. As we will show, the asymmetries between winner and loser return effects help to assess the degree to which tax loss trading accounts for the relation between past returns and expected returns.[7]

C. Behavioral Links Between Past Returns and the Cross-Section of Expected Returns

The profitability of momentum and contrarian trading strategies has been hard to justify under a rational pricing framework. For instance, the Sharpe ratio on a typical momentum strategy is about 2.5 times the Sharpe ratio of a typical broad-based stock index, which according to Mehra and Prescott (1985) is already too high. Moreover, Moskowitz (1998) documents that momentum strategies appear to work best in recessions and when the market is doing poorly, making its large risk premium even more puzzling when one considers the predictions of consumption-based asset pricing models.

Because such findings appear inconsistent with risk-based explanations for this phenomenon, recent models of momentum and reversals have emerged that are based on investor behavior that is not fully rational. Among these are models by Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999). Each of these models focuses on particular constraints on investor rationality that cause an underreaction of prices in the short-run, producing return persistence, and a subsequent overreaction to information in the long-run, producing reversals.[8] In addition, several recent empirical studies seem to promulgate a behavioral

[7]Grundy and Martin (1999) also document a significant negative momentum effect in January for the 1-year strategy, but do not examine end-of-year returns or attempt to link these phenomena to tax-loss trading.

[8]In the case of Daniel, Hirshleifer, and Subrahmanyam (1998), investors suffer from overconfidence and self-attribution biases, and in the Barberis, Shleifer, and Vishny (1998) model, the representative investor exhibits conservatism and representativeness biases, which cause short-term price underreaction and long-term price overreaction. In Hong and Stein (1999), the slow diffusion of information into prices causes an initial underreaction, but the presence of "momentum traders" seeking to exploit this slow price movement causes subsequent reversals.

interpretation of return autocorrelation puzzles. Among them are Hong, Lim, and Stein (1999) and Lee and Swaminathan (1999). For example, Hong, Lim, and Stein (1999) document that momentum is stronger among small stocks with low analyst coverage, which they interpret as firms with slow information diffusion, and hence stronger underreaction. Lee and Swaminathan (1999) find that firms with high stock turnover/trading volume also exhibit larger momentum.

II. Data Description

Our sample employs monthly returns from every listed security on the CRSP data files from August, 1963 to July, 1995. From 1963-1973, the CRSP sample includes NYSE and AMEX firms only, while post-1973, NASDAQ-NMS firms are added to our sample. In addition, we obtain industry returns by using two digit Standard Industrial Classification (SIC) groupings to form twenty value-weighted industry portfolios. The industries are those used in Moskowitz and Grinblatt (1999), and we refer the reader to their paper for a description of and summary statistics on these industry portfolios. Data on book-to-market equity make use of Compustat. Institutional ownership data, available from January 1980 on, are computed from Standard & Poors. Volume data, used from January 1976 on, comes from CRSP. Tax rates, used to identify tax regime subsamples, were obtained from Pechman (1987) and Willan (1994). Unless otherwise specified, our tests pertain to all NYSE, AMEX, and NASDAQ-NMS firms that possess the necessary data to compute the variables we employ in subsequent regressions (e.g., three years of past returns, book value of equity, one year of past trading volume data).

III. The Cross-Section of Expected Returns: Fama-MacBeth Regressions

A. Regression Description

Table I reports the time-series average of the coefficients along with time-series test statistics for a set of cross-sectional regressions run every month on all CRSP-listed stocks. The column labels identify the regressor associated with the coefficients. Panel A reports results from these "Fama-MacBeth (1973) regressions," computed from the August 1966 through July 1995.[9] The functional

[9]While the Compustat data begins in August 1963, we need three years of past return data to compute one of our variables. No CRSP-listed stock has this prior to August 1966 and no CRSP-listed NASDAQ firm has this prior to January 1976. For this reason, we start our analysis with a three-year delay.

form of the month t cross-sectional regression is

$$\tilde{r}_t(j) - \tilde{R}^h_t(j) = \alpha_t + \beta_{1t} r^W_{t-t1:t-t2}(j) + \beta_{2t} r^L_{t-t1:t-t2}(j) + \beta_{3t} D^{CW}_t(j) + \beta_{4t} D^{CL}_t(j) \qquad (1)$$

The dependent variable is stock j's month t return less the month t return on stock j's hedge portfolio, which is designed to offset the return component of stock j due to size, book-to-market (BE/ME), and industry premia. The hedge portfolio is based on an extension of the matching procedure used in Daniel and Titman (1997).[10] We employ this characteristically-matched portfolio adjustment method as opposed to a regression on pre-specified factor portfolios (i.e., Fama and French (1993)), in order to allow for time variation in a firm's exposure to these effects, to avoid estimation issues regarding factor loadings, and because Daniel and Titman (1997) argue that characteristics better capture cross-sectional variation in mean returns than do factor loadings during our sample period. The expected value of our dependent variable is zero if size, book-to-market, and industry are the only attributes that affect the cross-section of expected stock returns.[11] We also note that although there is no direct hedging of beta risk, the dependent variable is very close to a zero beta portfolio.[12]

The first pair of return regressor derive from the $t2 - t1 + 1$ month cumulative return on the stock from months $t - t2$ to $t - t1$ ($r_{t-t1:t-t2}$, with $t2 \geq t1$). This cumulative return is broken into both winner and loser return components, based on the sign of the past return. Specifically,

$$r^W_{t-t1:t-t2} = max(r_{t-t1:t-t2}, 0) \qquad (2)$$

$$r^L_{t-t1:t-t2} = min(r_{t-t1:t-t2}, 0). \qquad (3)$$

The subsequent pair of regressors, are two dummy variables indicating whether the stock was a consistent winner (D^{CW}) or consistent loser (D^{CL}) between months $t - t2$ and $t - t1$, which we

[10] The Daniel and Titman (1997) procedure adjusts returns for size and BE/ME by first sorting all stocks into size quintiles, and then within each size quintile, sorting stocks into BE/ME quintiles. Candidate hedge portfolios are formed by value-weighting the stocks within each of these 25 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. Size is the previous month's market capitalization of the firm, and BE/ME is the ratio of the firm's book value (defined as book value of equity plus deferred taxes and investment tax credits) divided by size, where BE is the most recent value prior to June of the current year. We then also subtract from this the return of a similarly size and book-to-market hedged industry portfolio. The stocks in the industry portfolio are value-weighted and consist of all CRSP-listed stocks with available data on size and BE/ME that match the original stock's two-digit SIC code grouping, as given in Moskowitz and Grinblatt (1999).

[11] The value-weighted cross-sectional average of this variable has a time-series mean of -0.0001 with a standard deviation of 0.0035, and has a maximum value of 0.0158 (in June, 1977), and a minimum value of -0.0231 (in October, 1978).

[12] Including β, size, 12-month past industry return, 1-month past-industry return, and BE/ME attributes as regressors negligibly alters our results as the coefficients on these variables in the Fama-MacBeth regressions are very close to zero.

define shortly. The left hand side of Table I reports average coefficients from regressions that omit these consistency dummies. The right hand side of the table includes them. (All column labels in the table exclude the t subscript for brevity.)

The pair $-t1, -t2$ takes on the value $-1, -1$ in Panel A, which proxies for the Jegadeesh (1990) 1-month reversal effect, which may be due to bid-ask bounce and related liquidity effects. In this case, being a consistent winner simply means having a positive return in the prior month. For this horizon alone, the consistent losers dummy must be omitted to avoid perfect multicollinearity. If the two return variables are inadequate controls for market microstructure imparted biases, and if there is no real relation between the past 1-month return and expected returns, then we expect the 1-month winners dummy variable to have a negative coefficient due to liquidity effects.

In Panel B, the pair $-t1, -t2$ takes on the value $-2, -12$. The two return regressors here break up the Jegadeesh and Titman (1993) 1-year momentum effect into separate 1-year winners and losers return effects.[13] The return consistency dummies here proxy for the inverse of volatility and analyze the extent to which momentum profits arise from expected returns being a simple linear function of past (winner/loser) returns or if the consistency of the return series is important. The 1-year winner consistency dummy is 1 if the return of the stock was positive in at least 8 of the 1-year horizon's 11 months, while the loser consistency variable is 1 if the return was negative in at least 8 of these 11 months.

In Panel C, the pair $-t1, -t2$ takes on the value $-13, -36$.[14] The two return regressors here break up the DeBondt and Thaler (1985) 3-year reversal effect into separate 3-year winners and losers return effects. Consistent winners are stocks with positive returns in 15 of the 24 months from $t-36$ to $t-13$, while consistent losers are stocks with negative returns in at least 15 of these 24 months. This definition of consistency has approximately the same p-values for its tails as the 8 of 11 criterion used to define 1-year winner consistency. Given equal probability of a positive or negative return in any month, the probability of a firm experiencing at least 8 of 11 positive return months (or 15 of 24) is approximately 10% under a binomial distribution. Hence, the 8 of 11 and

[13] We employ the prior year as a ranking period since Moskowitz and Grinblatt (1999) document that 1-year individual stock momentum is the strongest among a host of past return variables, and, in fact, is the only individual stock momentum variable of significance once industry effects are accounted for. In addition, many studies, including those of Fama and French (1996), Carhart (1997), and Asness and Stevens (1996), focus on the 1-year effect, and others, including Grundy and Martin (1999), also find the 1-year effect to be the strongest ranking horizon for individual stocks. Skipping a month in forming the past "1-year" return eliminates a potential market microstructure bias and makes the regressor relatively orthogonal to the other regressors used.

[14] Skipping a year makes this "3-year" past return variable relatively orthogonal to the other two regressors.

15 of 24 criteria, while arbitrary, were chosen because they capture the top decile of consistent performance under the null.

B. Results from Fama-MacBeth Regressions

The left hand side of the first row of Table I Panel A documents a strong 1-month reversal effect. The corresponding rows and columns in Panels B and C indicate that there is a weaker 1-year momentum effect, and a still weaker 3-year reversal effect in individual stocks, all of which are statistically significant.

The seasonal pattern in Panel B is particularly interesting, with both the January losers and winners coefficients being negative. Jegadeesh and Titman (1993) suggest that the negative January profits from a momentum strategy may be due to the tendency of winners to trade at the ask price and losers to sell at the bid at the close of the last trading day in December (see Keim (1989)). This will induce negative autocorrelation in monthly returns from December to January. Since we skip a month before computing our past 1-year stock returns, Panel B's seasonal patterns are not susceptible to this bid-ask bounce, yet exhibit the same pattern.

The third column in Panels B and C indicates that from August 1966 through July 1995 the average winner coefficient is statistically indistinguishable from the average loser coefficient. The apparent similarity of winner and loser effects here is sometimes masked by the seasonal patterns of these effects. For example, as noted above, the 1-year momentum effect reverses in January, more strongly for losers than for winners. When we separate these results into January-only, December-only, and February-November averages, we find that loser effects tend to be stronger than winner effects, particularly in December and January. On the other hand, from February through November,the 3-year reversal effect for winners is statistically indistinguishable from that for losers.

The prevailing wisdom is that the DeBondt and Thaler (1985) 3-year reversal is primarily driven by extreme losers. While this may be true for January, which has a losers effect that is six times the winners effect, it does not apply the rest of the year. For example, the December 3-year losers coefficient is not only positive, indicating persistence, but it is about eight times the size of the winners coefficient in December.[15] As we will discuss shortly, the positive long-term losers

[15] This may be sample specific, since the DeBondt and Thaler (1985) long-run reversal effect is weak over the 1963-1995 time period. Another possibility is that the long-run reversals are captured by the effects of size and BE/ME, as suggested by Kothari and Shanken (1999) and Fama and French (1996).

effect in December is consistent with year-end tax loss selling.

The addition of consistency dummies scarcely alters the coefficients on the two past returns regressors. However, for all three horizons, consistent winners outperform other stocks, ceteris paribus, generally with high significance. Consistent losers have no impact on returns at the two longer horizons. This suggests that the impact of winner consistency is not due to the lower volatility associated with consistency, which would apply to both losers and winners; rather, it reflects a more complex past returns effect.

The superior performance of winners at the 1-month horizon, where such an effect is indistinguishable from a losers effect, is rather surprising. The coefficient on this dummy variable is contaminated by a market microstructure bias. The imparted bias is towards a coefficient of opposite sign to that observed.

C. Tax Loss Trading and Seasonal Patterns

It is interesting to speculate about whether the seasonal pattern in the coeffients reported in Table I can be explained by tax loss selling – an end-of-December sell-off of losing stocks for tax purposes, which is magnified by the lower liquidity in financial markets at the end of the year. Although evidence of high returns in January supports this story, to date there has been little evidence of a December effect for stock returns. However, Table I documents a significant December effect for both 1- (Panel B) and 3-year losing stocks (Panel C). If the market for such stocks is particularly illiquid at the end of December, then the tax loss trading behavior could generate price patterns that are consistent with loser persistence in December and January reversals. The observed seasonal pattern in losing stocks, both over the 1- and 3-year past return horizons, as represented by the coefficients on $r^L_{-2:-12}$ and $r^L_{-13:-36}$, exhibit this price pattern.

The effect of tax loss trading on the seasonal return pattern of winning stocks is more ambiguous. On the one hand, full utilization of the tax write offs for realized capital losses requires that there be a realized capital gain of equal or greater size. It is most efficient to achieve this with stocks that have been the biggest winners. On the other hand, investors have generally been able to carry losses backward and forward to other tax years to some extent. These investors, as well as those with no capital losses, should be reluctant to sell winning stocks to avoid realizing capital gains. We believe that, on balance, the latter is the more relevant effect. Hence, it is not surprising that Panels B and C show that the coefficient on the past winning returns over both the

1- and 3-year horizons is largest in December (with a positive coefficient rather than the normally negative coefficient, as noted above).

Finally, there is evidence in Table I Panel A that is consistent with the conjecture that the end of December coincides with a particularly illiquid market. The coefficients on both $r^W_{-1:-1}$ and $r^L_{-1:-1}$, which may be due to a liquidity effect (e.g., see Kaul and Nimalendran (1990)), are most negative in January, but exhibit fairly similar magnitudes across the other months.

D. Combining Various Past Return Horizons in a Multiple Regression

It is worth noting that the effects of the nonoverlapping past return horizons are relatively independent. Table II Panel A combines all 11 regressors in the three panels of Table I in a single multiple regression. Observe that the Table II coefficients are similar to those in Table I. While the three sets of regressors, corresponding to Panels A, B, and C of Table I, are not perfectly orthogonal to one another, any correlation between regressors of various horizons appears to be swamped by the volatility of the regressors. Hence, as Table II Panel A confirms, we obtain similar results with regressions whether we combine horizons or not. For brevity, future analysis looks at all of the horizon effects simultaneously.

E. Changes in the Federal Tax Code for the Treatment of Capital Gains and Losses

If the seasonals in the coefficient pattern observed above are generated by tax loss selling, then the economic impact of such selling should be greater in high tax years than in low tax years. Specifically, tax-loss selling should contribute to the observed momentum in stock returns in December and the subsequent reversals in January. This is particularly true for stocks that have done poorly and thus are most likely to be sold at the end of the year, generating a further reduction in price due to year-end selling pressure and a bounceback in January.

Panels B and C of Table II investigate this hypothesis. Specifically, they report the average coefficients for two subsamples – “high tax years,” in Panel B, which represent the 2 years after a short-term capital gains tax increase or 2 years before a short-term capital gains tax decrease – and “low tax years,” Panel C, which represent the 2 years after a short-term capital gains tax decrease or 2 years before a short-term capital gains tax increase. These increases and decreases are based on a year-by-year comparison of the top U.S. Federal income tax rates. Our analysis concludes that high tax rate years correspond to 1968-70,[16] 1977-78, 1981, 1987-88, and 1993-94. The low tax years are 1966-67, 1971-72, 1979, 1982-83, and 1985-86. The remaining "neutral years," 1973-76, 1984, and 1989-92, are not in Panels B or C. Also, by our definition, 1980 is both a high tax year and a low tax year and is therefore left out as well. Finally, in determining whether a particular January belongs in Panel B or Panel C, we assign the respective January to the year of its adjacent December. For example, January 1993 is left out of the analysis because December 1992 belongs to a left out year, whereas January 1979 is a high-tax observation because 1978 is a high tax year.

Note from the December coefficients in Panels B and C that we have a larger losers persistence effect in high tax years than in low tax years. This is true for both 1-year losers, as exemplified by the coefficients on $r^L_{-2:-12}$, and 3-year losers, as shown by the coefficients on $r^L_{-13:-36}$. The coefficient pattern on the 3-year losing returns, although consistent with a tax story, is a bit surprising because we based our division of high and low tax years on the short term capital gains rate, rather than the long term one.

The winner effects in December are statistically insignificant. By contrast, in January, 1-year winning stocks have a reversal that is statistically significant in the high tax years and negligibly different from zero in the low tax years. This coefficient pattern is consistent with investors deferring their capital gains realizations until January of the new tax year in high tax regimes, especially when capital gains rates are expected to decrease.

Except for single months, like January and December, inferences about the impact of the tax regime on returns, obtained by analyzing differences in the average Fama-MacBeth coefficients across tax regimes are complicated by hindsight bias. For example, if information that tax rates are about to decline comes out in a high tax regime month, the winning stocks of profitable companies are likely to be helped more than the losing stocks of low or no profit companies. Similarly, information that taxes will increase hurts winning stocks more than losing stocks, reducing the profitability of momentum strategies. Another example is the ambiguity in the arrow of causation. For example, if momentum in winning stocks affects the distribution of wealth, tax rates may change to redistribute that wealth in a manner that restores the status quo. We believe that the January or December price patterns are unlikely to be affected by these considerations, but the same cannot be said for longer stretches of time. For this reason, we hesitate to draw conclusions

[16] While this consists of two pairings, 68-69 and 69-70, we count 1969 only once in our averages.

about the reasons for differences in the 1-year winners effect. Indeed, and consistent with this caution, we note that much of the discrepancy across tax regimes from February through November is generated by the years prior to a tax change, rather than the years after.

F. Exchange Listing

In the prior two subsections, the Fama-MacBeth regression analysis employs NYSE-AMEX stocks from 1966 to 1976 and both NYSE-AMEX and NASDAQ-NMS stocks from 1976 on. There are substantial differences between NASDAQ and the two more established exchanges. The NASDAQ-NMS, particularly in the later part of our sample period, contains more stocks than the NYSE and AMEX combined, most of them relatively small in market capitalization (although recall that we hedge out the size component of returns on the left hand side). NASDAQ also concentrates more in what may be considered growth industries (although recent IPOs are excluded from the analysis and value vs. growth is hedged out with industry and book-to-market matched portfolios). Finally, NASDAQ is based on a dealer system rather than a specialist system and has a lower proportion of institutional ownership than the more established exchanges.

To analyze if these differences across exchanges are associated with differences in the relation between past returns and the cross-section of expected returns, Table III reports the coefficients for the same Fama-MacBeth regression used in Table II. The coefficients are reported separately for NYSE-AMEX listed stocks over the entire sample period (Panel A), for NYSE-AMEX listed stocks from 1966-1975 (Panel B), for NYSE-AMEX listed stocks from 1976-1995 (Panel C), and for NASDAQ-NMS listed stocks from 1976-1995 (Panel D).

A comparison of the first row of Table III Panel A with the first row of Table II Panel A indicates that for NYSE-AMEX stocks the coefficient on 1-year loser momentum is larger and the coefficients on the three winner consistency dummies are smaller than they are for the overall sample. Indeed, at 1- and 3-year past return horizons, there is no significant winners consistency effect overall, although the 1-year consistency effect shows up from February through November among the NYSE-AMEX stocks. Panel A of Table III also indicates that for the more established exchanges, the 3-year loser reversal effect ($r^L_{-13:-36}$) disappears (although the January and opposite December effects are still there, consistent with tax-loss driven trades). The coefficient on the two past 1-month return variables are of the same magnitude in Tables II and III, which casts some doubt on a liquidity explanation for this reversal. If anything, the NASDAQ stocks should have larger liquidity-based reversals.

Panel C, when contrasted with Panel B, illustrates that among NYSE-AMEX stocks, the 3-year reversal discovered by DeBondt and Thaler (1985) is substantially weaker from 1976 on. This is consistent with prior research. However, as we will see shortly, this reversal is still prevalent in the more recent time period among NASDAQ stocks. Other than the coefficients on the three 1-month variables, which may be contaminated by market microstructure related biases, there are no other differences here that could not be due to chance, especially when accounting for the multiple test statistics analyzed.

Panel D of Table III, when compared to Panel C, suggests that the Fama-MacBeth coefficients for NASDAQ stocks generally exhibit a stronger relation between past returns and current returns than those for NYSE-AMEX stocks over the same time period. For example, consistent winners coefficients are about 3 to 10 times larger for NASDAQ stocks than for NYSE-AMEX stocks. The 3-year reversal for both past winners and especially losers also exists among NASDAQ stocks. However, the 1-year winners momentum effect is about half as large among the NASDAQ stocks as it is among the NYSE-AMEX sample.[17]

NASDAQ stocks generally show the same calendar patterns as the NYSE-AMEX stocks. The 1-month reversals are strongest in January. December losers show a pronounced 1-year momentum effect, consistent with tax loss selling. However, note the absence of a December 1-year momentum effect among the NYSE-AMEX stocks. This may be a chance event or it may reflect an ambiguity in the theoretically correct relation between past winner returns and current returns (arising from the two opposite tax effects discussed earlier). The contrast between December and the rest of the year for the 3-year past return relation also differs between Panels C and D. For the 3-year losers, both NASDAQ and NYSE-AMEX stocks show a large difference between December and the rest of the year, but the effect is only significant among the NYSE-AMEX stocks.

If tax loss selling is responsible for the persistent December returns among the NYSE-AMEX stocks, we would expect to find greater persistence among the NASDAQ firms because of their lower liquidity and their relatively more taxable clientele. The insignificance of the 57 basis point

[17]The lesser 1-year momentum effect is consistent with Hong, Lim, and Stein's (1999) finding that the 1-year past returns effect is a reversal within the very smallest NASDAQ firms. Since the regression likely picks up these extreme securities, our results may be driven by these firms. However, the seasonal pattern we document is not consistent with the behavioral story of Hong, Lim, and Stein (1999) – one where analysts dispense good news quickly while withholding bad news, an agency problem that is likely to be more acute in small, neglected firms.

3-year NASDAQ losers coefficient in December, while curious, does not necessarily contradict the tax loss selling hypothesis. This 57 basis point figure is still 140 basis points larger than the February-November coefficient. Any NASDAQ tax loss selling may have to contend with whatever economic force is generating the 3-year NASDAQ stock reversal in non-December months of the year assuming, quite reasonably, that such a force is present in December as well. This economic force, which does not seem to be prevalent among the NYSE-AMEX stocks from 1976-85, may account for the insignificance of the December coefficient on the 3-year NASDAQ loser returns.

IV. Measuring the Expected Return Impact of Past Price Movements

To better quantify the impact of past returns on expected returns, this section uses predicted returns from the Fama-MacBeth regressions described earlier to rank stocks and form portfolios. The predicted returns are determined by the beginning-of-month regressor values for the corresponding stocks, and, for the in-sample results, use average coefficients from all months in the same season – either January, February-November, or December – to weight the regressor values. The coefficients for ranking stocks are obtained from regressions involving all stocks. The ranked stocks are then grouped into rank-based deciles, with decile 10 having the highest predicted return, and value-weighted within each decile.

A. Portfolio Performance from Stock Rankings Based on the Fama-MacBeth Regressions

Panel A of Table IV reports in-sample results for the average monthly returns and annualized standard deviations of 10 zero- cost portfolios. Each portfolio is a value-weighted portfolio of the hedged positions in stocks in the corresponding decile. The returns of the hedged positions measure the deviations of the stock return from the return of a book-to-market, size, and industry matched portfolio, as described earlier. As noted above, the deciles in Table IV Panel A are obtained using the three sets of coefficients. Table IV Panel A portrays the average returns of a trading strategy that uses the January coefficients from Table II Panel A for January rankings, the February-November coefficients from Table II Panel A for ranking stocks from February through November, and the December coefficients for ranking stocks in December. The average returns and standard deviations of the decile portfolios formed from this dynamic trading strategy are reported in the first two rows of Table IV Panel A. The two rows below these break up the average returns and standard deviations into value-weighted portfolios of stocks within each decile that are not consistent winners (NC) and stocks that are consistent winners (C). In Panel A, the stock return is a consistent winner if it is a consistent winner over all three past return horizons.[18]

We can see from the first row of Panel A that the deciles are strictly monotonic. The lowest decile portfolio (Portfolio 1) loses 44 basis points per month on average and the highest-ranked portfolio (Portfolio 10) on average earns 90 basis points per month. Hence, controlling for size, book-to-market, and industry, the best-ranked portfolio outperforms the worst-ranked portfolio by over 130 basis points per month. The annualized return standard deviation of the ten hedged decile portfolios is slightly U-shaped, but there is much more volatility in the portfolios predicted to have the highest returns than those with the lowest return. Portfolio 10, generating almost 12% per year, is notably more risky than the other nine hedged portfolios.

Consistent winning stocks outperform other stocks in all but the seventh decile portfolio, and then only underperform by a mere 12 basis points per month. As might be expected, the percentage of the portfolio's market capitalization associated with consistent winning stocks increases with the portfolio number. Consistent winning stocks account for only 3.72% of Portfolio 1's market capitalization; they account for 51.09% of Portfolio 10's market capitalization.

The more than 130 basis point per month spread between Portfolios 1 and 10 in the first row of Panel A could partly be due to market microstructure effects. In particular, we noted that the past 1-month return may be negatively related to the current month return because of bid-ask bounce and related liquidity effects. For this reason, Panel B analyzes a scoring system with coefficients identical to that in Table IV Panel A, except that the coefficients on the three 1-month past return variables are set to zero. The average return and standard deviation pattern of the decile portfolios generated by the market microstructure-free variables are still rather remarkable. At over 115 basis points, the spread between Portfolios 1 and 10 is of similar magnitude to the spread in Panel A. The standard deviation pattern is also similar. As before, Portfolio 10, at 10.6% per year, exhibits a higher standard deviation than the other deciles. Except for the 8th decile portfolio, consistent winners outperform other stocks in each of the decile portfolios. Here, consistent winners are those stocks having positive returns in 8 of the 11 months from months -2

[18] The measured standard deviations of the returns of the consistent and inconsistent components of the decile portfolios are tied to the degree of diversification, and being misleading, are omitted.

through -12 and in 15 of the 24 months from months -13 through -36.

The large economic magnitude of the 1-month reversal makes the similarity between the market microstructure tainted results of Panel A and the microstructure free results of Panel B somewhat surprising. The similarity between the results in Panels A and B of Table IV is largely because value-weighting within the decile ranks greatly minimizes the impact of contaminating market microstructure effects. Although we do not report this as a table, equal-weighting within the deciles, rather than value-weighting, increases the spread between Portfolios 10 and 1 in Panel A to an enormous 277 basis points per month. However, the comparable equal-weighted spread in Panel B (excluding the 1-month return variables) drops to 171 basis points per month.[19]

To assess the relative economic importance of the 1- and 3-year horizons, Panels C and D of Table IV analyze the profitability of the Fama-MacBeth scoring system using only the coefficient estimates on the four 1-year horizon variables (Panel C) or the four 3-year horizon variables (Panel D) to form value-weighted decile portfolios. The remaining coefficient estimates from the first row of Table II Panel A are set to zero. The average returns of the decile portfolios in each panel are perfectly monotonic in Panel C and relatively monotonic in Panel D. The standard deviations are relatively U-shaped in Panel C with portfolio 10 exhibiting the greatest riskiness. In Panel D, Portfolio 10, which contains stocks with the most negative 3-year returns, again has the highest volatility at 8.7% per year. However, the U-shaped pattern is less evident. The largely appreciated stocks, decile portfolios 1-4, have volatilities that range from 4-5% per year. The declining stocks, in portfolios 6-9 have annualized volatility in the 5%-8% range, with little pattern within the two portfolio groups. This is consistent with the long held finding that stocks with rising prices tend to have lower volatility than other stocks.

A comparison of Panels C and D indicates that 1-year momentum is the stronger effect with a spread of almost 80 basis points per month between Portfolios 10 and 1. The 3-year reversals have a spread of about 20 basis points, about one-quarter the size of the momentum profitability. Partly, this may be because the 3-year reversal effect is known to be concentrated in the extremes, and largely applies to small-cap stocks. An equal-weighting within the deciles generates an approximately 80 basis point spread between Portfolios 10 and 1 in Panel D. However, we know that momentum is also a stronger economic effect among small stocks. An equal weighting of the stocks

[19] Surprisingly, Portfolio 10, equal weighted, has a standard deviation of only 12.0% per year despite an average return of 218 basis points per year.

within the deciles of Panel C also generates a much larger spread between Portfolio's 10 and 1 – in this case over 150 basis points. This suggests that despite the spread moderation generated by value-weighting, 1-year momentum has a stronger effect on stock returns than 3-year reversals.

B. Seasonalities in the Economic Importance of Each of the Past Price Variables

Panel A of Table V reports in-sample results for the average monthly returns and annualized standard deviations of four zero-cost portfolios. The first row of the left hand side of Panel A summarizes the information in Table IV, reporting the difference between Portfolios 10 and 1. Each column corresponds to a respective panel in Table IV. In addition to reporting the average spread between Porfolios 10 and 1, Panel A of Table V also reports the time series standard deviation of the spread. It also decomposes these average spreads and standard deviations into January-only, February-November only, and December-only statistics. The right hand side of Panel A reports the same information for the 1976-1995 subperiod, which is the period during which NASDAQ stocks are employed in the portfolios. The in-sample results for 1976-1995, which are similar to the results in the overall sample period, are used for comparison with out-of-sample results reported later in the paper. Here, we will concentrate on the four left columns of Panel A.

Observe that January and December are the most profitable times for the strategies. January accounts for about a third of the annual profit for the strategies employed in the first three columns and almost all of the profit for the long-term reversal. Although the latter result is partly an artifact of value-weighting within the deciles, the 3-year reversal is rather weak outside of January and nonexistent most of the year. Although January is important for all of the strategies, the similarity of the January average returns in the first two columns of Panel A indicates that market microstructure tainted returns do not drive the exceptional performance of these strategies. We also cannot attribute the performance of these strategies to a small firm effect, in that these returns are hedged against size and other factors and are based on value-weighting within the decile portfolios.

C. Average Returns for the Ranking System in Relation to Firm Size, Institutional Ownership, Book-to-Market, and Trading Volume

Although size and book-to-market return premia are controlled for in the previous analysis by examining the hedged returns of stocks, it is interesting to see if our trading strategies perform better among stocks that differ along these and other dimensions. Furthermore, this analysis may shed light on tax loss selling and other explanations that have been offered for the relation between past returns and expected returns.

Panel B of Table V repeats the exercise in Panel A, but employs subsamples based on firm size quintiles, with the quintiles generated by NYSE breakpoints. The left side of the panel represents the smallest market cap quintile and the right side represents the largest. According to Panel B, the profitability of all four investment strategies increases if we restrict investment to the smallest quintile and diminishes (but not entirely) if we restrict investment to the largest quintile of firms. For example, in the second and sixth columns, observe that a strategy focused on 1-year momentum and 3-year reversals earns 224 basis points per month when applied to only the smallest quintile of stocks, but only 60 basis points per month when applied to the largest quintile. In the largest quintile, the addition of the 1-month past return to the scoring system (5th column) only negligibly enhances the profitability of the strategy. Within the smallest quintile, the 1-month reversal effect enhances the spread between Portfolios 10 and 1 by more than 100 basis points per month.

Except for the pure 3-year reversal strategy, the profits of which are largely driven by January to begin with, the increased spread between Portfolios 10 and 1 among the smallest quintile stocks (relative to the largest quintile) in Panel B is not driven by any one particular season. However, the greatest spread differences between the size groupings arise in December and January. The stronger December persistence and January bounceback among the smallest firms is consistent with tax loss trading, since small stocks have more volatile prices (and therefore are more likely to be big winners or losers) and are owned by a larger fraction of individual investors who face capital gains taxation. On the other hand, the stronger profits for small stocks during the rest of the year is consistent with the findings of Hong, Lim, and Stein (1999) and may be due to other sources.

Since institutional investors are likely to be less concerned about capital gains taxes, examining how a stock's institutional ownership affects strategy profitability helps identify whether tax motivated trades drive the relation between past and future returns. Panel C of Table V repeats the exercise in Panel B, but employs subsamples based on institutional ownership, which represents the fraction of a firm's shares held by institutions, as reported by Standard & Poor's. If tax motivated trading is responsible for some of the observed relation between past returns and expected returns, then this relation should be strongest among firms with low institutional ownership.

To control for the potentially confounding effect of firm size, Panel C reports profits for strategies restricted to firms belonging to various size and institutional ownership groupings. Due to data limitations, the analysis here is from 1980 on. Five institutional ownership quintiles are generated within the smallest and largest third of stocks, reported on the left and right hand side of Panel C, respectively. The breakpoints for the five institutional ownership quintiles are those that generate equal numbers of firms within the respective size category, and are thus size quintile specific. For small stocks, low institutional ownership enhances the profitability of the strategies, except for the pure 3-year reversal strategy. This is especially true in January and December, a finding that is consistent with the results in Sias and Starks (1997), (who observe that abnormal January returns are larger for stocks with lower institutional ownership and interpret this is as evidence of a connection between tax-loss selling and the January return premium). However, within the largest quintile of stocks, institutional ownership has a mixed effect. The market microstructure contaminated "all" strategy is modestly more profitable among stocks with less institutional ownership, but the opposite is true, even in January, for a pure momentum strategy, and there is no effect of institutional ownership on the profitability of the remaining two strategies. We can only speculate as to the reasons for this. It is known that mutual funds, which concentrate in large cap stocks, tend to follow and profit from momentum strategies.[20] Possibly, their behavior is exacerbating the 1-year momentum effect.

Panel D of Table V repeats the exercise in Panel C, but employs subsamples based on book-to-market quintiles. Within the smallest market cap third of stocks, the investment strategies employed seem to be modestly more profitable when applied to low book-to-market stocks. Differences in the efficacy of these strategies across book-to-market quintiles within the largest cap stocks are similar, but even more modest than among the smallest cap stocks. Among the large cap stocks, the 1-year momentum and combined 1-year momentum and 3-year reversal strategies appear modestly more profitable among the lowest book-to-market quintile, and not because of December or January. In fact, the January success of these strategies seems to be strongest within the highest book-to-market quintiles.

Panel E of Table V employs subsamples based on trading volume, defined as the number of shares traded per day as a fraction of the number of shares outstanding, averaged over the prior

[20] See Grinblatt, Titman, and Wermers (1995). However, there is little evidence that other institutions like pension funds, employ momentum strategies.

months from $t-12$ to $t-2$. This definition of trading volume is similar to the one employed by Lee and Swaminathan (1999), who show that this measure has low correlation with firm size. Lee and Swaminathan (1999) examine NYSE-AMEX traded stocks and find that momentum and subsequent 3-year reversals are stronger among stocks with high trading volume (turnover), mostly driven by the performance of high volume losers. Examining NASDAQ-NMS stocks, however, we find quite different results. Trading volume is not comparable between stocks listed on NASDAQ and those listed on either the NYSE or AMEX exchanges.[21] For this reason, we average returns for high volume and low volume stocks separately for NYSE-AMEX stocks and for NASDAQ-NMS stocks, making the breakpoints for the volume quintiles exchange specific. In general, the investment strategies generate higher returns among high volume stocks, consistent with Lee and Swaminathan (1999). However, much of the added profitability among high volume stocks is due to performance at the turn of the year. Among NASDAQ-NMS firms, for instance, the profitability of 1-year momentum is enhanced by high trading volume, but this is all due to January and December. In fact, from February to November, low volume momentum stocks outperform high volume momentum stocks. This is inconsistent with Lee and Swaminathan (1999), yet supports the tax story, since high volume firms are those that were traded most heavily and thus provide the most likely candidates to be sold to offset capital gains at the end of the year. Likewise, December exhibits the greatest increase in profitability among high volume stocks traded on the NYSE-AMEX, consistent with year-end tax loss selling. However, the January bounceback among high volume firms is only stronger among NASDAQ-NMS stocks. The 3-year reversal effect is also stronger among high volume NASDAQ-NMS firms, except in December when the reversal effect switches sign due to tax loss selling. In addition, most of the added profitability of 3-year reversals among high volume stocks on NASDAQ is due to January, and the only month where high volume reversals are greater than low volume reversals on NYSE-AMEX occurs in January. This further supports our tax loss selling hypothesis and is inconsistent with Lee and Swaminathan (1999). However, we do note that among NYSE-AMEX stocks, high volume stocks still outperform low volume stocks from February to November, which may imply other factors (such as those in Lee and Swaminathan (1999)) besides tax loss selling may be contributing to these results.

[21]Due to the dealer system, each NASDAQ trade is generally counted twice and sometimes more, exaggerating trading volume relative to the traditional exchanges.

D. Out of Sample Results

Perhaps it is not surprising that the profitability of the trading strategies in the previous section are so strong. The scoring system that generates the ranks for the stocks was derived from the same sample of data used to assess profitability. Moreover, our specification for the scoring system, while not involving dozens of regressions, dispensed with some regression specifications that remain unreported, and more importantly, employs variables known to be related to average returns from previous studies.[22] It is therefore difficult to assess whether the implied trading strategies in the previous section are so successful because the variables analyzed are related to ex-ante expected returns, or because they are related to ex-post returns by chance. For example, a recent paper by Sullivan, Timmerman, and White (1999) suggests that calendar effects in stock returns, like the anomalous January effect, can be generated purely by data snooping.

If the success of our specification of the regressors was the product of an intensive search for the most marketable (or publishable) trading strategy using past literature as a guide, one would expect that the results obtained here would be substantially weaker if we perturb the trading strategies and weighting schemes and test them out of sample.

Table VI reports out-of-sample results for a modest perturbation of the implied trading strategy. In each calendar year beginning in 1976, we use the average coefficients from the 60 Fama-MacBeth monthly regressions run in the prior five years, separately averaging January, February-November, and December. The table is analogous to the right hand side of Table V Panel A, in that it only implements the trading strategy from January, 1976 to December, 1995. However, the in-sample results from Table V are based on the average of the Fama-MacBeth coefficients over the entire 30-year sample period from 1966 to 1995, separately averaging the January, February-November, and December coefficients. The results in Table VI, by contrast, average coefficients over rolling 5-year subperiods. In Panel A, the coefficient averages for the strategy in a given calendar year employ only the prior five years of coefficients for scoring and ranking stocks. Hence, in 1976, stock rankings in January, as well as December, are based on averaging the coefficients of five cross-sectional regressions, those for January 1971-1975 in the case of the January strategy and December 1971-1975 in the case of the December strategy. The strategies for February through November average the fifty monthly February-November coefficient vectors from 1971-1975. Panel

[22]For example, volatility, as measured by the variance of the past year's monthly returns, was a variable that was included in a specification of the regression, but never seemed to be related to average returns.

B is analogous to Panel A, except that a more distant 5-year period from 1966 to 1970 is used for scoring and ranking stocks for the 1976 strategy. For the 1977 strategy, Panel A employs coefficients from 1972-1976 for its average, while Panel B implements a 5-year lag and thus uses coefficients from 1967-1971. Each year, the coefficient averaging horizon rolls over by one calendar year for each panel, until the final year is reached.

This out-of-sample procedure has two implications. First, the out-of-sample results should be inferior to the in-sample results. This is both because there is no overlap between the test period for the strategy and the coefficient formation period and because the out-of-sample coefficient averages use less data (5 years) as opposed to the in-sample averages (30 years) and, containing more noise, should be less effective. The second implication is that if there is no real relation between past returns and current returns, there should be little difference between the profitability of the investment strategies in Panel's A and B. Both have similarly imprecise coefficient averages for stock rankings, and both use the same time period for out-of-sample testing.

This does not imply that there is no data snooping generating our out-of-sample returns. Our work rides on the shoulders of a body of research which largely employed the same dataset, and 5-year averages of coefficients are certainly going to generate results that are correlated with those findings. Nevertheless, if the relation between past and future returns is purely a data snooping phenomenon, we would expect the opposite of what we actually find in Panels A and B of Table VI. Looking at the first column in Panel A, we see that there is a mere 10 basis point deterioration from the in-sample results (from Table V Panel A – 4th column) for the first strategy, but a 21 basis point decline for the more relevant, microstructure-uncontaminated second strategy. With pure 1-year momentum, the deterioration from the in-sample strategy is a mere 12 basis points. Moreover, most of this deterioration is due to the highly imprecise January and December coefficients, which are averaged from only five regressions. When we look at February through November, we see that the pure 1-year strategy earns 5 basis points more out of sample than in sample.

Punctuating this is the comparison of Panels A and B from Table VI, which indicates that the observed structural relation between past and future returns is persistent. When the more distant 5-year returns are used, the profitability of the first strategy deteriorates by 34 basis points, and by 32 basis points for the second strategy. From February-November, the 1-year strategy's coefficients only earn 7 basis points per month in Panel B. This indicates that the proximity of the estimation period to the out-of-sample test period is more important than the difference between using five and twenty years of data combined with testing out of sample vs. in sample. Table VI thus suggests that data snooping cannot explain our findings.[23]

V. Conclusion

This paper presents a comprehensive analysis of the relation between the cross-section of past returns and the cross-section of expected returns. Past research has largely been unable to:

1. Describe whether profits from momentum and reversal strategies are due to winners or losers
2. Control for size, book-to-market, and industry effects simultaneously
3. Account for the mix between seasonal anomalies and past return anomalies
4. Understand how tax regimes affect observed returns from momentum and reversal strategies
5. Analyze how market microstructure and the effects at various horizons interact to affect conclusions about the profitability of trading strategies that make use of technical analysis
6. Examine how data snooping might alter the conclusions.

We have attempted to address all of these issues in this paper. We have also tried to illustrate that the relation between past and future returns is complex, affected both by the sign of the return and the consistency of the sequence of past monthly returns. The tax-loss selling story is supported by many of our results. We find for example, that momentum and reversals are more strongly concentrated among losing firms in December and January. We also show that momentum investment strategies produce their greatest profits at the end of the year, and greatest losses at the beginning of the year. We also find that contrarian investment strategies produce their greatest losses at the end of the year and greatest profits at the beginning of the year. These seasonal patterns are exacerbated when tax rates are higher.

Armed with these empirical facts, we demonstrate that one can generate highly profitable trading strategies (even after controlling for size, BE/ME, and industry return premia) based on simple technical trading rules. These technical trading strategies seem to work best on small firms, small firms with few institutional investors, growth firms, and firms with high trading volume.

[23] Jegadeesh and Titman (1999) also document that momentum strategies are equally profitable over the 1990-1998 time period as they were over their original sample period from 1963-1989, providing further out-of-sample evidence diminishing data snooping concerns.

Moreover, the performance of these strategies cannot entirely be attributed to data snooping. Admittedly, the findings of other researchers played a role in our selection of variables. While there is little we can do about this aspect of data snooping, we show that there is persistence in the structure of the relation between the cross-section of past returns and the cross-section of future returns and that this persistence is a more important determinant of profitability than the degree of data snooping. These findings pose a challenge to explanations for intermediate-term momentum and long-term reversals related to behavioral biases. These theories do not predict a strong difference between the performance of winners and losers, do not predict any seasonal patterns in this performance, and make no predictions about the strength of these seasonal effects in various tax regimes.

Our findings suggest that tax-loss selling contributes substantially to the observed autocorrelation in stock returns. Additional anecdotal evidence from other studies may provide further support for tax-loss trading as an important component of return autocorrelation puzzles. For instance, both Daniel (1996) and Haugen and Baker (1996) document negligible momentum in Japan. This, however, may be due to the fact that the Japanese tax code did not tax capital gains for individual investors before 1989. Finally, as documented in Conrad and Kaul (1998), among others, there is little momentum in stock returns in the pre-war era (1925-1943), yet strong long-term reversals are present during this time. However, prior to 1942, short-term losses could only be used to offset short-term gains, implying a weaker incentive for investors to realize short-term losses.

On the other hand, tax-loss selling does not completely explain these autocorrelation puzzles, and even if it did, tax-loss selling will only provide a rational resolution to these puzzles when the trading frictions that prevent investors from arbitraging away these well documented seasonal patterns are identified. As Shleifer and Vishny (1997) suggest, exploring the limits to arbitrage activity that prevent this seasonal pattern from disappearing is an open question for future research.

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Table I:
Winner, Loser, and Consistency Effects of Past Return Variables Across Seasons

Fama and MacBeth (1973) cross-sectional regressions are run every month on all NYSE, AMEX, and NASDAQ securities from August, 1966 to July, 1995. The cross-section of stock returns, adjusted for size, BE/ME, and industry effects at time t are regressed on a constant (omitted for brevity) and a host of past return variables. The adjusted return for a stock is its time t return minus the return on a hedge portfolio of similar size, book-to-market, and industry attributes. Panel A reports average coefficients from two regressions of the cross-section of hedged stock returns on the independent variables associated with 1-month reversals. The first regression includes only the return on the stock from the previous month ($r_{-1:-1}$), separated into winner and loser return components by truncating returns above and below zero. The second regression adds a dummy variable D^{CW}_{1mo}, indicating whether the stock had a positive return last month. Panel B employs two regressions using the independent variables associated with 1-year momentum. The first regression includes only the cumulative return on the stock from month $t-12$ to month $t-2$ ($r_{-2:-12}$), separated into winner and loser return components, and the second regression adds two dummy variables indicating whether the stock was a 1-year consistent winner (D^{CW}_{1yr}) or loser (D^{CL}_{1yr})– respectively defined as any stock exhibiting positive returns in at least 8 of the 1-year horizon's 11 months or exhibiting negative returns in at least 8 of these 11 months. Panel C employs two regressions using independent variables associated with 3-year reversals. The first regression includes only the cumulative return on the stock from month $t-36$ to $t-13$ ($r_{-13:-36}$), separated into winner and loser components, and the second regression adds two dummy variables indicating whether the stock was a 3-year consistent winner (D^{CW}_{3yr}) or loser (D^{CL}_{3yr}), respectively defined as any stock exhibiting positive returns in at least 15 of the 3-year horizon's 24 months or exhibiting negative returns in at least 15 of these 24 months. The average coefficients and time-series t-statistics (in parentheses) are reported for these regressions over all months, for the month of January only, from February to November only, and for December only. In addition, the difference between winner and loser return coefficients are reported along with t-statistics in parentheses.

Cross-Section of Size, BE/ME, and Industry Hedged Returns

Panel A: 1-Month Reversals

	$r^W_{-1:-1}$	$r^L_{-1:-1}$	$r^L - r^W$	$r^W_{-1:-1}$	$r^L_{-1:-1}$	D^{CW}_{1mo}		$r^L - r^W$
All	-0.0388	-0.1086	-0.0698	-0.0494	-0.1190	0.0049		-0.0696
	(-10.03)	(-12.29)	(-7.05)	(-12.67)	(-12.85)	(8.50)		(-6.98)
Jan.	-0.0536	-0.3788	-0.3253	-0.0598	-0.3859	0.0046		-0.3261
	(-3.21)	(-8.54)	(-6.98)	(-3.34)	(-7.99)	(1.59)		(-7.05)
Feb.-Nov.	-0.0381	-0.0820	-0.0439	-0.0493	-0.0940	0.0050		-0.0446
	(-9.04)	(-10.61)	(-4.62)	(-11.70)	(-11.36)	(8.42)		(-4.63)
Dec.	-0.0428	-0.0960	-0.0531	-0.0573	-0.1090	0.0072		-0.0517
	(-3.19)	(-3.33)	(-1.80)	(-4.74)	(-4.02)	(3.30)		(-1.84)

Panel B: 1-Year Momentum

	$r^W_{-2:-12}$	$r^L_{-2:-12}$	$r^L - r^W$	$r^W_{-2:-12}$	$r^L_{-2:-12}$	D^{CW}_{1yr}	D^{CL}_{1yr}	$r^L - r^W$
All	0.0047	0.0111	0.0064	0.0041	0.0102	0.0029	-0.0012	0.0061
	(4.00)	(2.76)	(1.47)	(3.35)	(2.50)	(3.94)	(-1.17)	(1.38)
Jan.	-0.0002	-0.1079	-0.1078	-0.0011	-0.1052	0.0026	0.0020	-0.1042
	(-0.04)	(-4.25)	(-4.15)	(-0.25)	(-4.00)	(0.66)	(0.50)	(-3.88)
Feb-Nov.	0.0046	0.0198	0.0152	0.0039	0.0183	0.0033	-0.0017	0.0145
	(3.53)	(6.12)	(3.95)	(2.89)	(5.61)	(4.13)	(-1.56)	(3.69)
Dec.	0.0076	0.0461	0.0386	0.0075	0.0469	0.0012	0.0016	0.0393
	(1.87)	(4.00)	(3.42)	(1.94)	(4.16)	(0.45)	(0.54)	(3.54)

Panel C: 3-Year Reversals

	$r^W_{-13:-36}$	$r^L_{-13:-36}$	$r^L - r^W$	$r^W_{-13:-36}$	$r^L_{-13:-36}$	D^{CW}_{3yr}	D^{CL}_{3yr}	$r^L - r^W$
All	-0.0012	-0.0072	-0.0060	-0.0014	-0.0082	0.0013	-0.0009	-0.0069
	(-2.32)	(-2.43)	(-1.88)	(-2.65)	(-2.79)	(2.42)	(-1.06)	(-2.16)
Jan.	0.0020	-0.0925	-0.0945	0.0020	-0.0873	-0.0021	0.0081	-0.0893
	(0.90)	(-5.43)	(-5.15)	(1.01)	(-5.11)	(-0.85)	(1.59)	(-4.86)
Feb.-Nov.	-0.0020	-0.0013	0.0006	-0.0021	-0.0026	0.0015	-0.0014	-0.0005
	(-3.52)	(-0.53)	(0.23)	(-3.76)	(-1.03)	(2.73)	(-1.60)	(-0.18)
Dec.	0.0026	0.0206	0.0180	0.0022	0.0179	0.0025	-0.0042	0.0157
	(1.32)	(2.44)	(1.88)	(1.19)	(2.27)	(1.11)	(-1.47)	(1.74)

Table II:
Seasonal Patterns and Tax Code Changes on Past Return Variables

Fama and MacBeth (1973) cross-sectional regressions are run every month on all NYSE, AMEX, and NASDAQ securities from August, 1966 to July, 1995. The dependent variable is the cross-section of stock returns at time t minus the return on a hedge portfolio of similar size, book-to-market, and industry attributes. The independent variables are the return on the stock from the previous month ($r_{-1:-1}$), a dummy variable indicating whether the stock had a positive return in the previous month (D^{CW}_{1mo}), the cumulative return on the stock from month $t-12$ to month $t-2$ ($r_{-2:-12}$), two dummy variables indicating whether the stock was a consistent 1-year winner (D^{CW}_{1yr}) or loser (D^{CL}_{1yr}) – respectively defined as any stock exhibiting positive returns in at least 8 of the 1-year horizon's 11 months or exhibiting negative returns in at least 8 of these 11 months, the cumulative return on the stock from month $t-36$ to $t-13$ ($r_{-13:-36}$), and two dummy variables indicating whether the stock was a consistent 3-year winner (D^{CW}_{3yr}) or loser (D^{CL}_{3yr}) – respectively defined as any stock exhibiting positive returns in at least 15 of the 3-year horizon's 24 months, or exhibiting negative returns in at least 15 of these 24 months. The past return variables $r_{-1:-1}$, $r_{-2:-12}$, and $r_{-13:-36}$ are separated into winner and loser return components by truncating returns above and below zero. The average coefficients and time-series t-statistics (in parentheses) are reported for this multivariate regression over all months, for the month of January only, from February to November only, and for December only. Panel A reports the time-series average coefficients over the whole sample period (August, 1966 to July, 1995). Panel B reports the time-series average coefficients over "high tax years" – defined as the two years after a short term capital gain tax increase or two years before a short term capital gain tax decrease. These years are 1968-70, 1977-78, 1981, 1987-88, and 1993-94. Panel C reports the time-series average coefficients over "low tax years" – defined as the two years before a short term capital gain tax increase or two years after a short-term capital gains tax decrease. These years are 1966-67, 1971-72, 1979, 1982-83, and 1985-86. The short-term capital gains tax rates used to determine these subsamples are those of the highest marginal tax bracket.

	Cross-Section of Size, BE/ME, and Industry Hedged Returns										
	$r^W_{-1:-1}$	$r^L_{-1:-1}$	D^{CW}_{1mo}	$r^W_{-2:-12}$	$r^L_{-2:-12}$	D^{CW}_{1yr}	D^{CL}_{1yr}	$r^W_{-13:-36}$	$r^L_{-13:-36}$	D^{CW}_{3yr}	D^{CL}_{3yr}
	Panel A: Whole Sample										
All	-0.0476	-0.1237	0.0050	0.0028	0.0141	0.0043	-0.0008	-0.0016	-0.0076	0.0012	-0.0008
	(-11.63)	(-15.97)	(8.62)	(2.43)	(3.90)	(5.64)	(-0.79)	(-3.52)	(-3.07)	(2.34)	(-0.92)
Jan.	-0.0969	-0.3234	0.0089	-0.0071	-0.0804	0.0104	0.0044	-0.0002	-0.0581	0.0025	0.0104
	(-4.33)	(-9.23)	(2.56)	(-1.85)	(-3.83)	(2.37)	(1.19)	(-0.12)	(-4.28)	(1.24)	(2.00)
Feb.-Nov.	-0.0445	-0.1039	0.0048	0.0029	0.0201	0.0042	-0.0014	-0.0022	-0.0049	0.0010	-0.0015
	(-10.62)	(-13.97)	(8.48)	(2.32)	(6.33)	(5.28)	(-1.33)	(-4.29)	(-2.11)	(1.88)	(-1.77)
Dec.	-0.0434	-0.1342	0.0061	0.0072	0.0528	0.0014	0.0012	0.0022	0.0172	0.0009	-0.0041
	(-3.69)	(-5.90)	(3.03)	(2.01)	(5.21)	(0.56)	(0.41)	(1.31)	(2.77)	(0.51)	(-1.44)
	Panel B: High Tax Years										
All	-0.0303	-0.1035	0.0024	-0.0005	0.0235	0.0049	0.0008	-0.0015	-0.0050	0.0020	-0.0008
	(-3.87)	(-8.79)	(2.77)	(-0.25)	(4.51)	(4.54)	(0.55)	(-4.18)	(-1.16)	(3.21)	(-0.71)
Jan.	-0.0642	-0.2549	0.0015	-0.0123	-0.0444	0.0128	0.0132	-0.0005	-0.0327	-0.0008	-0.0053
	(-1.74)	(-8.48)	(0.40)	(-2.44)	(-3.85)	(1.54)	(2.85)	(-0.36)	(-1.51)	(-0.33)	(-0.98)
Feb.-Nov.	-0.0310	-0.0914	0.0031	-0.0006	0.0239	0.0048	-0.0009	-0.0018	-0.0036	0.0024	0.0010
	(-3.59)	(-7.08)	(3.18)	(-0.25)	(4.38)	(4.68)	(-0.55)	(-4.38)	(-0.79)	(3.36)	(0.81)
Dec.	-0.0168	-0.1079	0.0025	0.0017	0.0825	0.0015	0.0011	-0.0002	0.0346	0.0022	-0.0090
	(-0.61)	(-2.12)	(0.99)	(0.39)	(5.29)	(0.41)	(0.28)	(-0.19)	(3.81)	(1.21)	(-1.98)
	Panel C: Low Tax Years										
All	-0.0475	-0.1045	0.0036	0.0067	0.0212	0.0028	-0.0020	-0.0025	-0.0070	0.0015	-0.0019
	(-7.33)	(-7.78)	(4.01)	(3.54)	(3.93)	(2.83)	(-1.09)	(-2.34)	(-1.62)	(1.83)	(-1.33)
Jan.	-0.0362	-0.2653	0.0016	-0.0003	-0.0224	-0.0012	0.0013	-0.0010	-0.0462	0.0014	0.0087
	(-1.41)	(-4.76)	(0.39)	(-0.04)	(-0.87)	(-0.30)	(0.17)	(-0.22)	(-2.08)	(0.39)	(0.88)
Feb.-Nov.	-0.0516	-0.0905	0.0044	0.0059	0.0226	0.0042	-0.0014	-0.0031	-0.0029	0.0016	-0.0027
	(-7.29)	(-6.90)	(4.30)	(3.16)	(4.36)	(4.13)	(-0.67)	(-3.04)	(-0.69)	(1.78)	(-1.44)
Dec.	-0.0502	-0.0866	0.0034	0.0105	0.0351	-0.0011	0.0023	0.0038	0.0110	0.0011	0.0001
	(-2.12)	(-3.80)	(1.10)	(1.71)	(2.08)	(-0.36)	(0.46)	(0.75)	(1.35)	(0.41)	(0.02)

Table III:
Seasonal Patterns in Past Return Variables Across Exchanges

Time-series average coefficients and t-statistics (in parentheses) from the Fama-MacBeth cross-sectional regressions used in Table II are reported separately for NYSE-AMEX listed stocks from August, 1966 to July, 1995 (Panel A), for NYSE-AMEX listed stocks from August, 1966 to December, 1975 (Panel B), for NYSE-AMEX listed stocks from January, 1976 to July, 1995 (Panel C), and for NASDAQ-NMS listed stocks from January, 1976 to July, 1995 (Panel D). Average coefficients are reported over all months, for January only, for February through November only, and for December only.

	Cross-Section of Size, BE/ME, and Industry Hedged Returns										
	$r^W_{-1:-1}$	$r^L_{-1:-1}$	D^{CW}_{1mo}	$r^W_{-2:-12}$	$r^L_{-2:-12}$	D^{CW}_{1yr}	D^{CL}_{1yr}	$r^W_{-13:-36}$	$r^L_{-13:-36}$	D^{CW}_{3yr}	D^{CL}_{3yr}
Panel A: NYSE-AMEX (Aug., 1966 - July, 1995)											
All	-0.0602	-0.1051	0.0025	0.0041	0.0266	0.0014	0.0010	-0.0013	-0.0051	0.0007	-0.0002
	(-11.47)	(-10.71)	(3.62)	(2.88)	(6.10)	(1.79)	(0.92)	(-2.45)	(-1.73)	(1.39)	(-0.24)
Jan.	-0.1255	-0.3017	0.0041	-0.0048	-0.0691	0.0007	0.0013	0.0011	-0.0652	-0.0038	0.0049
	(-4.73)	(-5.48)	(1.04)	(-0.78)	(-3.24)	(0.17)	(0.31)	(0.55)	(-5.32)	(-2.04)	(0.77)
Feb.-Nov.	-0.0552	-0.0859	0.0025	0.0047	0.0343	0.0018	0.0007	-0.0018	-0.0020	0.0013	-0.0006
	(-10.10)	(-9.43)	(3.68)	(2.99)	(8.07)	(2.23)	(0.55)	(-3.19)	(-0.68)	(2.27)	(-0.64)
Dec.	-0.0564	-0.1189	0.0033	0.0037	0.0570	-0.0022	0.0074	0.0015	0.0307	-0.0006	0.0002
	(-3.51)	(-3.35)	(1.37)	(0.98)	(4.30)	(-0.92)	(1.84)	(0.80)	(3.76)	(-0.41)	(0.06)
Panel B: NYSE-AMEX (Aug., 1966 - Dec., 1975)											
All	-0.0586	-0.1090	0.0003	0.0047	0.0231	0.0030	0.0024	-0.0033	-0.0095	0.0000	0.0003
	(-4.88)	(-5.80)	(0.25)	(1.35)	(2.84)	(1.62)	(1.58)	(-2.60)	(-1.68)	(-0.02)	(0.29)
Jan.	-0.1263	-0.4030	0.0056	-0.0212	-0.0850	0.0062	0.0074	-0.0003	-0.0750	-0.0039	-0.0025
	(-1.54)	(-3.90)	(0.76)	(-1.51)	(-1.75)	(0.57)	(1.42)	(-0.06)	(-2.96)	(-1.34)	(-0.75)
Feb.-Nov.	-0.0575	-0.0853	0.0001	0.0056	0.0319	0.0037	0.0028	-0.0050	-0.0060	0.0004	0.0015
	(-4.59)	(-4.88)	(0.13)	(1.37)	(4.29)	(1.74)	(1.65)	(-3.40)	(-1.05)	(0.33)	(1.36)
Dec.	-0.0426	-0.1208	0.0027	0.0113	0.0701	-0.0039	0.0051	0.0067	0.0343	-0.0013	-0.0007
	(-1.15)	(-2.22)	(0.53)	(1.22)	(2.22)	(-0.92)	(1.07)	(1.56)	(3.15)	(-0.30)	(-0.17)
Panel C: NYSE-AMEX (Jan., 1976 - July, 1995)											
All	-0.0610	-0.1033	0.0034	0.0038	0.0283	0.0006	0.0004	-0.0004	-0.0031	0.0011	-0.0005
	(-11.38)	(-9.00)	(4.18)	(2.85)	(5.45)	(0.83)	(0.27)	(-0.74)	(-0.90)	(1.88)	(-0.36)
Jan.	-0.1251	-0.2561	0.0035	0.0026	-0.0619	-0.0018	-0.0015	0.0018	-0.0607	-0.0037	0.0082
	(-6.87)	(-3.89)	(0.70)	(0.43)	(-2.61)	(-0.60)	(-0.27)	(0.85)	(-4.20)	(-1.52)	(0.91)
Feb.-Nov.	-0.0526	-0.0825	0.0033	0.0047	0.0337	0.0010	-0.0007	-0.0005	-0.0013	0.0019	-0.0015
	(-8.85)	(-7.48)	(3.80)	(3.12)	(6.29)	(1.35)	(-0.40)	(-0.99)	(-0.37)	(3.18)	(-1.16)
Dec.	-0.0629	-0.1180	0.0035	0.0001	0.0508	-0.0013	0.0085	-0.0009	0.0289	-0.0003	0.0006
	(-3.62)	(-2.49)	(1.28)	(0.02)	(3.67)	(-0.44)	(1.51)	(-0.51)	(2.58)	(-0.25)	(0.12)
Panel D: NASDAQ-NMS (Jan., 1976 - July, 1995)											
All	-0.0374	-0.1484	0.0082	0.0021	0.0003	0.0070	-0.0026	-0.0013	-0.0085	0.0037	-0.0017
	(-7.77)	(-14.67)	(8.94)	(2.38)	(0.07)	(8.18)	(-1.33)	(-3.11)	(-3.10)	(4.39)	(-0.98)
Jan.	-0.0850	-0.3224	0.0144	-0.0019	-0.0753	0.0115	0.0012	-0.0012	-0.0321	0.0094	0.0119
	(-4.44)	(-7.51)	(3.35)	(-0.84)	(-4.05)	(2.58)	(0.15)	(-0.60)	(-2.75)	(2.58)	(1.20)
Feb.-Nov.	-0.0311	-0.1255	0.0074	0.0022	0.0061	0.0064	-0.0032	-0.0014	-0.0085	0.0034	-0.0027
	(-5.85)	(-11.85)	(7.19)	(2.20)	(1.81)	(6.93)	(-1.44)	(-3.12)	(-2.83)	(4.05)	(-1.47)
Dec.	-0.0493	-0.1760	0.0111	0.0065	0.0346	0.0073	0.0007	0.0002	0.0057	0.0037	-0.0038
	(-3.87)	(-6.07)	(4.90)	(2.16)	(2.96)	(3.55)	(0.12)	(0.19)	(0.67)	(1.31)	(-0.82)

Table IV:
Profits from In-Sample Fama-MacBeth Ranking System
(Value-Weighted)

Average monthly returns and annualized standard deviations of 10 zero-cost portfolios are reported over the August, 1966 to July, 1995 time period. Using the predicted returns from the multivariate regression of Table II Panel A, stocks are ranked each month and grouped into rank-based decile portfolios, with decile 10 having the highest predicted return. Each decile portfolio is a value-weighted portfolio of the hedged (with respect to size, BE/ME, and industry) positions in stocks in the corresponding decile. The time-series average of the regression coefficients are used to score stocks, where January coefficients are used for January rankings, February through November coefficients for February through November rankings, and December coefficients for December rankings. Average returns and annualized standard deviations (in parentheses) are reported over all months. Panel A uses all regression coefficients to score and rank stocks. Panel B excludes the three regression coefficients corresponding to the 1-month reversals to rank stocks. Panel C uses only the four regression coefficients corresponding to 1-year momentum to rank stocks, and Panel D uses only the four regression coefficients corresponding to 3-year reversals to rank stocks. For each panel, we also report the profits from those stocks that were not consistent winners (NC), and from only those stocks that were consistent winners (C). The value-weighted portfolios corresponding to the non-consistent and consistent only stocks are re-weighted to sum to one, and the percentage of the market capitalization of each of the decile portfolios that is accounted for by the consistent stocks (%C)is reported on the last line of each panel.

	Deciles									
	1	2	3	4	5	6	7	8	9	10
	Panel A: All Regressors									
	-0.0044	-0.0036	-0.0028	-0.0016	0.0006	0.0008	0.0025	0.0039	0.0062	0.0090
	(0.060)	(0.043)	(0.050)	(0.046)	(0.045)	(0.048)	(0.050)	(0.058)	(0.069)	(0.120)
NC	-0.0044	-0.0035	-0.0036	-0.0041	0.0004	0.0011	0.0032	0.0053	0.0054	0.0075
C	-0.0028	-0.0021	-0.0023	-0.0012	0.0005	0.0009	0.0020	0.0053	0.0074	0.0112
%C	3.72%	5.99%	8.10%	14.86%	24.42%	34.20%	44.44%	49.34%	49.00%	51.09%
	Panel B: Exclude 1-Month Reversals									
	-0.0050	-0.0039	-0.0027	-0.0009	-0.0010	0.0005	0.0021	0.0024	0.0035	0.0067
	(0.082)	(0.067)	(0.067)	(0.051)	(0.045)	(0.045)	(0.057)	(0.058)	(0.061)	(0.106)
NC	-0.0056	-0.0041	-0.0026	-0.0010	-0.0004	0.0002	0.0016	0.0032	0.0038	0.0046
C	-0.0048	-0.0045	-0.0042	-0.0004	-0.0002	0.0029	0.0022	0.0020	0.0040	0.0076
%C	27.96%	28.72%	29.21%	30.07%	29.83%	30.03%	34.07%	38.17%	57.64%	81.25%
	Panel C: 1-Year Momentum									
	-0.0026	-0.0022	-0.0018	-0.0014	-0.0011	-0.0007	0.0017	0.0034	0.0037	0.0052
	(0.068)	(0.056)	(0.059)	(0.042)	(0.045)	(0.047)	(0.057)	(0.057)	(0.064)	(0.087)
NC	-0.0028	-0.0022	-0.0017	-0.0013	-0.0009	-0.0008	0.0016	0.0034	0.0050	0.0013
C	0.0158	0.0078	0.0072	0.0012	-0.0042	0.0000	0.0044	-0.0077	0.0013	0.0031
%C	0.17%	0.27%	0.39%	0.49%	0.60%	1.89%	5.05%	12.34%	37.74%	75.81%
	Panel D: 3-Year Reversals									
	0.0003	0.0001	0.0000	-0.0024	-0.0001	-0.0011	0.0010	0.0014	0.0027	0.0022
	(0.052)	(0.042)	(0.050)	(0.053)	(0.070)	(0.054)	(0.067)	(0.063)	(0.078)	(0.099)
NC	0.0000	0.0000	0.0000	-0.0022	-0.0005	-0.0017	0.0012	0.0047	0.0040	0.0019
C	0.0019	0.0002	-0.0015	0.0020	0.0034	0.0007	-0.0040	-0.0003	-0.0098	0.0032
%C	28.69%	25.61%	23.30%	22.36%	20.72%	24.31%	24.77%	24.75%	20.60%	13.27%

Table V:
Contribution of Past Return Variables Across Stock Attributes

Using the predicted returns from the multivariate regression of Table II Panel A, stocks are ranked each month and grouped into rank-based decile portfolios, with decile 10 having the highest predicted return. Each decile portfolio is a value-weighted portfolio of the hedged (with respect to size, BE/ME, and industry) positions in stocks in the corresponding decile. The time-series average of the regression coefficients are used to score stocks, where January coefficients are used for January rankings, February through November coefficients for February through November rankings, and December coefficients for December rankings. Average monthly returns and annualized standard deviations of the spread between the best and worst-ranked decile portfolios are reported for various time periods and subsamples of stocks. Column 1 uses all regression coefficients to score and rank stocks, column two excludes the three regression coefficients corresponding to the 1-month reversals to rank stocks, column 3 uses only the four regression coefficients corresponding to 1-year momentum to rank stocks, and column 4 uses only the four regression coefficients corresponding to 3-year reversals to rank stocks. Panel A reports the profits on these zero-cost portfolios across all stocks over the period August, 1966 to July, 1995 and over the subperiod January, 1976 to July, 1995. Panel B reports the profits for the smallest and largest quintile of stocks (using NYSE market capitalization breakpoints) over the period August, 1966 to July, 1995. Panel C reports the profits for the lowest and highest quintile of stocks based on fraction of institutional ownership over the period January, 1980 to July, 1995. Stocks are first sorted by market capitalization, and profits are reported for the highest and lowest quintiles of institutional owership within the smallest and largest third of stocks. Panel D reports the profits for the lowest and highest quintiles of stocks based on book-to-market equity within the smallest and largest third of stocks over the period August, 1966 to July, 1995. Panel E reports the profits for the lowest and highest quintile of stocks based on trading volume (average share turnover over the past year) for NYSE-AMEX traded stocks and NASDAQ-NMS traded stocks separately over the period January, 1976 to July, 1995.

	All	Ex. 1-Month Reversals	1-Year Momentum	3-Year Reversals	All	Ex. 1-Month Reversals	1-Year Momentum	3-Year Reversals
				Panel A: All Stocks				
		(1966-1995)				*(1976-1995)*		
All	0.0133	0.0116	0.0077	0.0019	0.0112	0.0092	0.0064	0.0011
	(0.143)	(0.147)	(0.127)	(0.114)	(0.135)	(0.137)	(0.120)	(0.112)
Jan.	0.0586	0.0507	0.0207	0.0461	0.0433	0.0373	0.0145	0.0415
	(0.280)	(0.282)	(0.191)	(0.165)	(0.232)	(0.256)	(0.155)	(0.161)
Feb.-Nov.	0.0076	0.0073	0.0058	-0.0028	0.0071	0.0063	0.0035	-0.0031
	(0.112)	(0.117)	(0.117)	(0.098)	(0.116)	(0.113)	(0.116)	(0.099)
Dec.	0.0253	0.0174	0.0113	0.0033	0.0263	0.0145	0.0072	0.0017
	(0.126)	(0.161)	(0.150)	(0.081)	(0.133)	(0.162)	(0.143)	(0.081)
				Panel B: Size (Market Capitalization)				
		Smallest Quintile				*Largest Quintile*		
All	0.0340	0.0224	0.0177	0.0040	0.0060	0.0056	0.0062	0.0017
	(0.178)	(0.172)	(0.137)	(0.126)	(0.100)	(0.120)	(0.117)	(0.097)
Jan.	0.1168	0.0881	0.0560	0.0573	0.0292	0.0314	0.0209	0.0200
	(0.416)	(0.410)	(0.287)	(0.235)	(0.182)	(0.152)	(0.183)	(0.099)
Feb.-Nov.	0.0253	0.0138	0.0125	-0.0020	0.0029	0.0036	0.0044	-0.0005
	(0.104)	(0.103)	(0.103)	(0.094)	(0.086)	(0.114)	(0.108)	(0.095)
Dec.	0.0382	0.0390	0.0318	0.0083	0.0131	0.0021	0.0062	0.0038
	(0.103)	(0.134)	(0.109)	(0.080)	(0.081)	(0.120)	(0.119)	(0.092)

	Smallest Stocks (market cap.)				Largest Stocks (market cap.)			
	All	Ex. 1-Month Reversals	1-Year Momentum	3-Year Reversals	All	Ex. 1-Month Reversals	1-Year Momentum	3-Year Reversals
Panel C: Institutional Ownership								
Lowest Institutional Ownership Quintile								
All	0.0256	0.0232	0.0214	0.0001	0.0093	0.0066	0.0017	0.0012
	(0.165)	(0.175)	(0.133)	(0.135)	(0.157)	(0.150)	(0.149)	(0.131)
Jan.	0.1051	0.1080	0.0731	0.0562	0.0207	0.0364	0.0193	0.0223
	(0.319)	(0.370)	(0.265)	(0.197)	(0.229)	(0.188)	(0.159)	(0.155)
Feb.-Nov.	0.0151	0.0141	0.0147	-0.0064	0.0062	0.0030	-0.0016	0.0007
	(0.101)	(0.104)	(0.085)	(0.114)	(0.139)	(0.141)	(0.143)	(0.129)
Dec.	0.0383	0.0380	0.0241	0.0164	0.0139	0.0162	-0.0051	-0.0030
	(0.131)	(0.127)	(0.119)	(0.074)	(0.183)	(0.153)	(0.121)	(0.127)
Highest Institutional Ownership Quintile								
All	0.0158	0.0122	0.0121	-0.0008	0.0064	0.0053	0.0087	0.0016
	(0.183)	(0.157)	(0.154)	(0.164)	(0.120)	(0.121)	(0.117)	(0.090)
Jan.	0.0436	0.0194	0.0100	0.0302	0.0262	0.0282	0.0225	0.0219
	(0.177)	(0.223)	(0.155)	(0.143)	(0.187)	(0.191)	(0.139)	(0.111)
Feb.-Nov.	0.0114	0.0122	0.0121	-0.0035	0.0026	0.0045	0.0067	0.0010
	(0.179)	(0.150)	(0.149)	(0.156)	(0.100)	(0.110)	(0.101)	(0.086)
Dec.	0.0188	0.0142	0.0003	0.0059	0.0062	-0.0051	-0.0020	-0.0001
	(0.184)	(0.154)	(0.167)	(0.247)	(0.109)	(0.096)	(0.134)	(0.064)
Panel D: Book-to-Market Equity								
Lowest BE/ME Quintile								
All	0.0301	0.0220	0.0198	0.0052	0.0083	0.0082	0.0090	0.0008
	(0.183)	(0.180)	(0.148)	(0.143)	(0.130)	(0.147)	(0.135)	(0.121)
Jan.	0.1096	0.0758	0.0462	0.0580	0.0275	0.0282	0.0165	0.0274
	(0.399)	(0.383)	(0.267)	(0.225)	(0.227)	(0.191)	(0.204)	(0.121)
Feb.-Nov.	0.0219	0.0150	0.0162	0.0001	0.0048	0.0063	0.0077	-0.0021
	(0.121)	(0.133)	(0.126)	(0.121)	(0.115)	(0.141)	(0.127)	(0.118)
Dec.	0.0324	0.0394	0.0301	0.0055	0.0212	0.0086	0.0111	0.0016
	(0.135)	(0.163)	(0.153)	(0.110)	(0.115)	(0.143)	(0.135)	(0.106)
Highest BE/ME Quintile								
All	0.0273	0.0177	0.0130	0.0021	0.0081	0.0066	0.0038	0.0010
	(0.195)	(0.185)	(0.148)	(0.152)	(0.153)	(0.159)	(0.152)	(0.131)
Jan.	0.1027	0.0762	0.0473	0.0610	0.0420	0.0412	0.0195	0.0365
	(0.440)	(0.448)	(0.330)	(0.258)	(0.278)	(0.231)	(0.221)	(0.178)
Feb.-Nov.	0.0187	0.0107	0.0083	-0.0047	0.0063	0.0030	0.0015	-0.0009
	(0.130)	(0.119)	(0.106)	(0.122)	(0.130)	(0.149)	(0.146)	(0.120)
Dec.	0.0385	0.0319	0.0230	0.0138	-0.0038	0.0055	0.0091	-0.0122
	(0.135)	(0.152)	(0.146)	(0.110)	(0.144)	(0.141)	(0.134)	(0.121)

	NYSE-AMEX Stocks				NASDAQ-NMS Stocks			
		Ex. 1-Month	1-Year	3-Year		Ex. 1-Month	1-Year	3-Year
	All	Reversals	Momentum	Reversals	All	Reversals	Momentum	Reversals
	Panel E: Trading Volume (Stock Turnover)							
	Lowest Volume Quintile							
All	0.0095	0.0041	0.0054	0.0009	0.0136	0.0108	0.0088	0.0001
	(0.110)	(0.109)	(0.112)	(0.094)	(0.134)	(0.121)	(0.137)	(0.112)
Jan.	0.0353	0.0228	0.0151	0.0160	0.0225	0.0053	-0.0114	0.0069
	(0.204)	(0.134)	(0.141)	(0.095)	(0.144)	(0.135)	(0.135)	(0.160)
Feb.-Nov.	0.0066	0.0029	0.0046	-0.0010	0.0133	0.0099	0.0107	-0.0013
	(0.093)	(0.106)	(0.108)	(0.091)	(0.127)	(0.118)	(0.136)	(0.105)
Dec.	0.0167	0.0008	0.0001	0.0062	0.0169	0.0203	0.0099	0.0137
	(0.076)	(0.097)	(0.122)	(0.109)	(0.188)	(0.129)	(0.127)	(0.122)
	Highest Volume Quintile							
All	0.0173	0.0158	0.0098	0.0016	0.0378	0.0189	0.0112	0.0073
	(0.175)	(0.177)	(0.162)	(0.157)	(0.237)	(0.276)	(0.213)	(0.183)
Jan.	0.0545	0.0478	0.0154	0.0449	0.1292	0.1138	0.0341	0.0297
	(0.354)	(0.326)	(0.204)	(0.176)	(0.328)	(0.575)	(0.315)	(0.248)
Feb.-Nov.	0.0124	0.0130	0.0082	-0.0033	0.0279	0.0073	0.0060	0.0053
	(0.140)	(0.152)	(0.156)	(0.140)	(0.203)	(0.200)	(0.198)	(0.178)
Dec.	0.0220	0.0059	0.0158	-0.0030	0.0419	0.0417	0.0343	0.0089
	(0.172)	(0.175)	(0.175)	(0.207)	(0.237)	(0.276)	(0.240)	(0.182)

Table VI:
Profits from Out-of-Sample Fama-MacBeth Ranking System

Beginning January, 1976, the multivariate regression specification from Table II is run over either the previous five years of data (years -5 to -1 for Panel A) or over data from years -10 to -5 (for Panel B). Stocks are ranked each month in order of predicted return and grouped into rank-based deciles, with decile 10 having the highest predicted return. Each decile portfolio is a value-weighted portfolio of the hedged (with respect to size, BE/ME, and industry) positions in stocks in the corresponding decile. The time-series average of the regression coefficients are used to score stocks, where January coefficients are used for January rankings, February through November coefficients for February through November rankings, and December coefficients for December rankings. Average monthly returns and annualized standard deviations of the spread between the best and worst-ranked decile portfolios are reported. Column 1 uses all regression coefficients to score and rank stocks, column two excludes the three regression coefficients corresponding to the 1-month reversals to rank stocks, column 3 uses only the four regression coefficients corresponding to 1-year momentum to rank stocks, and column 4 uses only the four regression coefficients corresponding to 3-year reversals to rank stocks.

	All	Ex. 1-Month Reversals	1-Year Momentum	3-Year Reversals	All	Ex. 1-Month Reversals	1-Year Momentum	3-Year Reversals
	Panel A: Nearest 5-year Ranks				**Panel B: Distant 5-year Ranks**			
All	0.0102	0.0071	0.0052	0.0061	0.0068	0.0039	0.0036	0.0020
	(0.124)	(0.123)	(0.114)	(0.093)	(0.124)	(0.110)	(0.115)	(0.098)
Jan.	0.0293	0.0420	0.0136	0.0361	0.0435	0.0353	0.0092	0.0364
	(0.227)	(0.219)	(0.113)	(0.144)	(0.218)	(0.138)	(0.159)	(0.173)
Feb.-Nov.	0.0068	0.0044	0.0040	0.0041	0.0029	0.0007	0.0025	-0.0010
	(0.111)	(0.105)	(0.115)	(0.082)	(0.102)	(0.101)	(0.108)	(0.080)
Dec.	0.0186	0.0082	0.0104	-0.0039	0.0144	0.0081	0.0084	-0.0047
	(0.067)	(0.110)	(0.128)	(0.078)	(0.130)	(0.124)	(0.147)	(0.079)