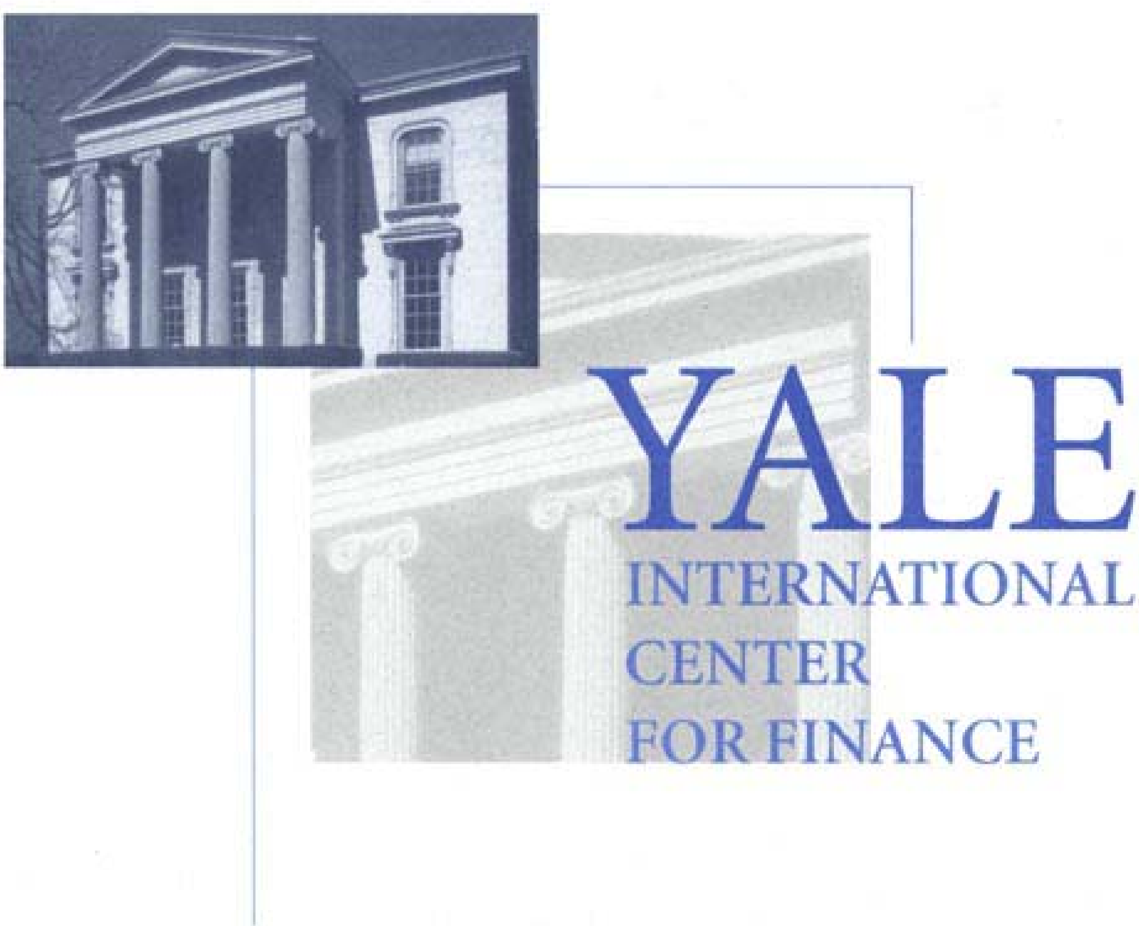


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# WHAT DO WE REALLY KNOW ABOUT THE CROSS-SECTIONAL RELATION BETWEEN PAST AND EXPECTED RETURNS?

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# What Do We Really Know About the Cross-Sectional Relation Between Past and Expected Returns?


## Abstract

Multihorizon temporal relationships between stock returns are complex due to confounding sources of return premia, microstructure effects, and changes in the relationship over various horizons. We find the relation to be further complicated by the sign and consistency of the past return that also varies, somewhat sensibly, with the season and the tax environment. Accounting for these additional effects using a parsimonious technical trading rule generates surprisingly large abnormal returns, despite controlling for microstructure effects, transaction costs, and data-snooping biases. The documented variation in profits across stock characteristics, season, and tax environment appear inconsistent with existing theory, but may point to future explanations for the relation between past and expected returns.

# 1. Introduction

How well do past returns predict future returns? This question has received much academic attention of late because of its implications for the weakest form of market efficiency. However, inferring the relation between past and expected returns has proven difficult due to the noise in realized returns and confounding sources of return premia.

Within the last fifteen years, researchers have discovered that past returns contain information about expected returns: Both short- (less than 1 month) 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] A variety of explanations have been offered for these relationships. They range from data issues, such as microstructure and data snooping biases,[2] to rational risk-based explanations,[3] to irrational behavioral stories.[4] However, it is difficult to reconcile the exceptional profits generated by trading strategies that exploit these patterns with theories of rational asset pricing or data-related biases. Consequently, models of irrational investor behavior have emerged as leading contenders to explain these phenomena. Only recently have these theories evolved to explain these patterns synthetically. Yet, little empirical work has analyzed these patterns simultaneously, and, as we will show, there are additional complexities to these relations that appear inconsistent with existing explanations. Before proposing novel theories for their existence or embarking on trades to potentially exploit them, it is important to attain a better understanding of these temporal relationships. This is the goal of this paper.

The relation between past returns and expected returns is complex in that stock return seasonalities, book-to-market effects, size effects, and industry effects all play a role in these relations.[5]

[1]Most studies focus on a particular aspect of this predictability pertaining to a single horizon. Classic papers include Jegadeesh (1990), DeBondt and Thaler (1985), and Jegadeesh and Titman (1993), respectively. Autocorrelation in stock returns at various horizons has also been documented by (among others) DeBondt and Thaler (1987), Lo and MacKinlay (1988), Conrad and Kaul (1989), Lehman (1990), Boudoukh, Richardson, and Whitelaw (1994a), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Hong, Lim, and Stein (2000), Grundy and Martin (2001), and Lee and Swaminathan (2000).

[2]See Boudoukh, Richardson, and Whitelaw (1994a), Conrad and Kaul (1989), and Lo and MacKinlay (1988).

[3]See Conrad and Kaul (1998) and Chordia and Shivakumar (2001).

[4]See DeBondt and Thaler (1985, 1987), Jegadeesh and Titman (1993), Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), Hong, Lim, and Stein (2000), and Lee and Swaminathan (2000).

[5]Keim (1983), Roll (1983), Lakonishok and Smidt (1988), and many others document predictable seasonal patterns in returns, Fama and French (1992, 1993, 1996) and many others demonstrate the power of size and book-to-market in explaining cross-sectional variation in average returns, and Boudoukh, Richardson, and Whitelaw (1994b) and Moskowitz and Grinblatt (1999) show the importance of industry effects in average returns and in the relation between past and expected returns, respectively.

To understand temporal relations between returns, it is important to address:

- The degree to which seasonalities, tax-motivated trading that may vary by tax regime, or common sources of variation like size, book-to-market, or industry drive these relations.
- Whether the past pattern of returns matters for predictability, including both the consistency and sign (direction) of past returns.
- Whether these patterns are more prevalent or exclusive to a particular segment of the market and how they interact with other firm characteristics.
- The extent to which data snooping has generated "discoveries" about temporal return relations or whether it is a real phenomenon that is likely to persist in the future.
- Whether the profitability of trading strategies based on past returns is primarily driven by buys or sells and if trading costs eliminate these profits.

In this paper, we take the perspective of a technical analyst with a scientific bent and explore these issues. This perspective provides several insights that might allow theory to properly model these complex relationships. We present a parsimonious stock ranking system derived from simple Fama-MacBeth cross-sectional regressions to form portfolios that capture the economic impact of the relation between past and expected returns. The profits from these portfolios are studied over a variety of subperiods and subclassifications of stocks, including an out-of-sample return period not previously examined. The profitability of our portfolios is quite remarkable, even after abstracting from microstructure influences and accounting for transaction costs.

The approach we take analyzes the simultaneous effect of all of the relevant past return variables on the future returns of *hedged* positions in individual stocks, which have their book-to-market, size, and industry return components eliminated and are beta neutral as well. This hedged stock approach can better assess the marginal impact of each past return variable on the cross-section of expected returns by eliminating confounding return premia and reducing volatility to generate more powerful tests. One startling finding about momentum that comes out of this is that winner consistency is important: Achieving a high past return with a series of steady positive months appears to generate a larger expected return than a high past return achieved with just a few extraordinary months. This may offer clues about the source of momentum profits.

By using returns that are adjusted to have expected values of zero, our approach also allows us to quantify asymmetric effects from past positive (winners) and negative (losers) returns and to illustrate how the asymmetry varies by season. In particular, our analysis is careful to differentiate return processes in different months, separating January, as well as December, from the rest of the year. For example, the asymmetric January effects for past winners and losers we document could distort the relative importance of past winners and losers if not accounted for.

We also show that seasonalities in stock returns are partly responsible for the profitability of technical trading strategies and may account for some of the findings of researchers in the past. The 3-year reversal is entirely a January-related effect during our sample period. It is therefore possible that research attempting to link long-term reversals to intermediate-term momentum is misguided. Similarly, value-weighted strategies developed from the past 1-year and past 3-year patterns do not exhibit significant profitability outside of January and December in low tax years. Perhaps explanations for these phenomena based on consistent biases in human behavior might take a back seat to traditional January effect explanations, like "window dressing" by institutional investors or tax-loss selling by individual investors.

In addition to confounding the temporal relation between returns, analyzing seasonalities may shed light on explanations for the seasonal effects themselves. 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), can be further enhanced by acquiring small firms with negative past returns, even after hedging out the small-firm, industry, and book-to-market premia that exist in January.[6] Since firm-specific risk is largely diversified away in our portfolio formation process, known priced common factors are hedged out, and market microstructure influences (in the sense of Keim (1989)) are alleviated, there must be some common component related to size and past return per se that drives the January return enhancement. This common attribute may be related to selling pressure from window dressing or tax-loss selling occurring at year-end.[7] If this is the case, such selling pressure should depress the share prices of small, poorly performing firms further in December. However,

[6] A host of papers analyze the "January effect", including Dyl (1977), Roll (1983), Keim (1983, 1989), Reinganum (1983), Berges, McConnell, and Schlarbaum (1984), Chan (1986), Lakonishok and Smidt (1988), Reinganum and Shapiro (1987), Dyl and Maberly (1992), and Poterba and Weisbenner (2000).

[7] 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), for instance.

to date, past research has not documented a great effect on December stock returns from such selling pressure. In contrast to earlier work, we find strong evidence of December effects from past returns that are generally of opposite sign from the effects of past returns in January. Both findings are consistent with year-end selling pressure being responsible for some of the profitability of technical trading strategies.[8]

To distinguish among various theories for these temporal relations, we also analyze the interaction between these patterns and other firm characteristics. The profitability of our technical trading strategies varies greatly depending on firm size, book-to-market ratio, institutional ownership, and turnover per year. Prior studies have often used these firm attributes to advance theories of why past returns predict future returns. It is therefore useful to analyze if these attributes are still of import when profitability measures control for other sources of return premia as well as return seasonalities. Our findings on which types of stocks lend themselves to the most profitable technical trading strategies provide additional evidence, some supportive and some contradictory, on previous theories advanced in the literature to explain why these temporal relations exist. These findings also seem to imply that a careful real-world implementation of such a strategy on selected stocks can earn even larger returns than those generated from the entire stock market.

For instance, we find that small, high turnover stocks with low institutional ownership exhibit more pronounced past return and seasonal effects. This suggests that tax-loss selling, as opposed to window dressing, contributes to these patterns. Moreover, we compare the December and January profitability of technical trading strategies in high- and low-tax years. Tax avoidance behavior, rather than window dressing, appears to be driving much of the relation between past returns and expected returns in December and January 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. When effective capital gains tax rates are expected to decrease (providing an incentive to accelerate the realization of losses), increased selling pressure on losing stocks improves the profitability of momentum strategies, but makes contrarian strategies relatively less profitable. Similarly, when expected tax code changes favor capital loss deferral, the opposite occurs: Contrarian strategies become relatively more profitable and the profits from momentum strategies decline. More generally, these findings pose a challenge

[8]By inferring buying and selling pressure from quoted daily spreads, Hvidkjaer (2001) documents year-end selling pressure in firms that have done poorly over the prior year and subsequent year-end buying pressure of these firms at the turn of the year. His patterns of trading mirror our seasonal return patterns.

to existing theory which makes no prediction regarding changes in the intertemporal relations between stock returns as the tax code changes.

The final contribution of this paper is that it addresses a central criticism of all research on stock return anomalies. This criticism arises because empirical researchers have largely focused on the same datasets of stock returns over the past two decades in searching for anomalies and patterns can be found, ex-post, in randomly generated returns if one searches intensely enough. In particular, the best ex-post fit of the data is not a good method for generating profitable technical trading strategies that will work ex-ante (what Lo and MacKinlay (1990) have termed "data snooping.") Using out-of-sample analysis, we find that data snooping biases cannot account for most of the profitability of our past returns portfolio strategies.

The paper is organized as follows: Section 2 briefly describes the data used in our empirical analysis. Section 3 reports both summary statistics along with the coefficients and test statistics for Fama-MacBeth regressions that describe how past returns affect the cross-section of expected returns. These coefficients also document how this relation varies seasonally. Section 4 examines the economic significance of the past-expected return relation by translating the Fama-MacBeth coefficients into a stock ranking system used to analyze how the best and worst scored stocks perform both in sample and out of sample. The degree to which market microstructure effects, various past return horizons, and trading costs affect profitability is also assessed. Section 5 analyzes the out-of-sample success of our strategies as well as which sectors of the stock market have expected returns that are most affected by past returns. Section 6 analyzes how changing tax regimes affect this relation. Finally, Section 7 summarizes our findings in relation to the literature and concludes the paper.

## 2. Data Description

Our sample employs monthly returns from every listed security on the Center for Research in Security Prices (CRSP) data files from August, 1963 to December, 1999. From 1963 to 1973, the CRSP sample includes NYSE and AMEX firms only, and post-1973 NASDAQ-NMS firms are added to the sample. Industry returns are obtained from two digit Standard Industrial Classification (SIC) groupings of stocks into twenty value-weighted industry portfolios as in Moskowitz and Grinblatt (1999). Data on book-to-market equity make use of Compustat, where book value of equity is the most recent value from the prior fiscal year. Institutional ownership data, available from January, 1981 on, are computed from Standard & Poors. Volume data for the turnover computation, used from January, 1976 on for NYSE-AMEX and from January, 1982 on for NASDAQ, comes from CRSP. Turnover is defined as the number of shares traded per day as a fraction of the number of shares outstanding, averaged over the prior twelve months. Tax rates, used to identify tax regime subsamples, are obtained from Pechman (1987) and Willan (1994) prior to 1995 and from the IRS after 1995. 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 (e.g., three years of past returns, book value of equity, one year of past trading volume history).

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

Consider an investor who has read some of the finance literature on the relation between past returns and the cross-section of expected returns. A sensible way for such an investor to develop a trading strategy based on this evidence would be to run cross-sectional regressions. In formulating a strategy it is important to benchmark returns for known sources of return premia. Hence, a reasonable dependent variable would be the difference between the return of a stock and the return of its benchmark portfolio. We refer to this adjusted return as a "hedged return," as it reflects the return of a stock position hedged by a position in its benchmark portfolio. We describe below how we compute these returns.

To understand the impact of past returns, the investor would probably investigate more than the simple relation derived from a linear regression of hedged returns on past returns. For example, he might want to test for differences in the impact of past positive and past negative returns and whether the impact of the past return on future returns is path dependent.

The finance literature has documented three past return horizons that are relevant. Returns from the past month seem to generate return reversals (losers outperform winners), while for returns extending out to a year in the past, there appears to be return persistence (winners outperform losers). At longer horizons, there are reversals again. It is sensible to analyze non-overlapping past return horizons to isolate these effects.

## 3.1. Regression Description

The functional form of the month $t$ cross-sectional regression that we will analyze is,

$$\begin{aligned}
\tilde{r}_t(j) - \tilde{R}^B_t(j) &= \alpha_t + \beta_{1t} r_{t-1:t-1}(j) + \beta_{2t} r^L_{t-1:t-1}(j) + \beta_{3t} D^{CW}_{t-1:t-1}(j) \\
&+ \gamma_{1t} r_{t-12:t-2}(j) + \gamma_{2t} r^L_{t-12:t-2}(j) + \gamma_{3t} D^{CW}_{t-12:t-2}(j) + \gamma_{4t} D^{CL}_{t-12:t-2}(j) \qquad (1) \\
&+ \delta_{1t} r_{t-36:t-13}(j) + \delta_{2t} r^L_{t-36:t-13}(j) + \delta_{3t} D^{CW}_{t-36:t-13}(j) + \delta_{4t} D^{CL}_{t-36:t-13}(j) \\
&+ \tilde{\epsilon}_t(j),
\end{aligned}$$

where

$$\begin{aligned}
\tilde{r}_t(j) &= \text{stock } j\text{'s return in month } t, \\
\tilde{R}^B_t(j) &= \text{stock } j\text{'s benchmark portfolio return in month } t, \\
r_{t-t2:t-t1}(j) &= \text{stock } j\text{'s ``buy and hold'' cumulative return from month } t-t2 \text{ to month } t-t1, \\
r^L_{t-t2:t-t1}(j) &= min(0, r_{t-t2:t-t1}(j)), \text{ the cumulative return from month } t-t2 \text{ to month } t-t1 \\
&\quad \text{for negative (loser) returns only (otherwise it is zero)}, \\
D^{CW}_{t-t2:t-t1}(j) &= \text{a dummy variable that is one if stock } j \text{ is a consistent winning stock over the} \\
&\quad \text{horizon } t-t2 : t-t1 \text{ (to be defined shortly, zero otherwise) and} \\
D^{CL}_{t-t2:t-t1}(j) &= \text{a dummy variable that is one if stock } j \text{ is a consistent losing stock over that horizon.}
\end{aligned}$$

The pair $t-t2, t-t1$ takes on the value $t-1, t-1$ when it proxies for the 1-month reversal discovered by Jegadeesh (1990). The reversal may be due to bid-ask bounce and related liquidity effects,[9] so we exclude this horizon in some tests. We define being a consistent winner at the 1-month horizon as simply having a positive return in the prior month. (For this horizon alone, it is necessary to omit the consistent losers dummy to avoid perfect multicollinearity.)

When $t-t2, t-t1$ is $t-12, t-2$, the regressors' coefficients are analyzing the marginal effect of the past 1-year return – the momentum effect of Jegadeesh and Titman (1993).[10] The return

[9]For example, Kaul and Nimalendran (1990), Asness (1995), Lo and MacKinlay (1988), Boudoukh, Richardson, and Whitelaw (1994a), and Ahn, Boudoukh, Richardson, and Whitelaw (2000) argue that a significant component of short-term return reversals is driven by liquidity effects or microstructure biases such as bid-ask bounce.

[10]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 (2001), 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 past 1-month return regressors used.

consistency dummies here may proxy for the inverse of volatility and test whether the information about expected returns contained in the past 1-year of price movements is more complex than past research seems to indicate. The 1-year winner consistency dummy is one if the monthly return of the stock was positive in at least 8 of the 1-year horizon's 11 months, while the loser consistency variable is one if the monthly return was negative in at least 8 of the past 11 months.

When the pair $t-t2, t-t1$ is $t-36, t-13$, we are analyzing the marginal effect of the past 3-year return – the long-term reversal effect studied by DeBondt and Thaler (1985).[11] 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 consistency.[12]

The dependent variable is a hedged return: stock $j$'s month $t$ return less the month $t$ return of stock $j$'s benchmark portfolio, which is designed to offset the return component of stock $j$ due to size, book-to-market (BE/ME), and industry effects. The benchmark portfolio is based on an extension and variation of the matching procedure used in Daniel and Titman (1997) and is designed to hedge out the expected return of stock $j$, except for the marginal effect of stock $j$'s past return per se on its return premium.

To form the benchmark portfolios for our hedged returns, we first independently sort all CRSP-listed firms each month into size and BE/ME quintiles, based on NYSE quintile breakpoints for firm size and CRSP universe quintile breakpoints for book-to-market. 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 group every CRSP-listed firm into one of 25 size- and BE/ME groupings based on the intersection between the size and book-to-market independent sorts. Because size and book-to-market are not truly independent, the number of stocks within each of the 25 groupings vary.[13] Within each of the 25 groupings, we

[11] As before, skipping a year generates orthogonality with the regressors at other horizons.

[12] 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 15 of 24 criteria, while arbitrary, were chosen because they capture the top decile of consistent performance under the null.

[13] An earlier draft of this paper also used the sequential sort procedure in Daniel and Titman (1997), which generates approximately equal numbers of stocks in each of the 25 benchmark portfolios. The results are similar to those presented here.

value weight based on market capitalization at the beginning of the month, forming 25 benchmark portfolios. Note that each CRSP-listed stock belongs to one unique portfolio of the 25. To form a size and BE/ME hedged return for any stock, we simply subtract the return of the portfolio to which that stock belongs from the return of the stock. Although this generates a return difference that is size and book-to-market neutral, the return difference does not control for the effect of a stock's own industry return.

Since a three-way sort using industry membership, in addition to size and book-to-market, would place too few stocks in many of the portfolios (sometimes zero), we neutralize returns for industry effects by additionally subtracting the return of a stock's size- and BE/ME-neutral industry portfolio. The latter is simply a market cap weighting of the size- and BE/ME-hedged returns of the stocks in the firm's own industry, as defined by the 2-digit SIC industry groupings of Moskowitz and Grinblatt (1999). Hence, $R_t^B(j)$ is the sum of the return on stock $j$'s size- and BE/ME-matched portfolio and the return on its size- and BE/ME-adjusted industry portfolio.

The expected value of our dependent variable is zero if size, book-to-market, and industry membership are the only attributes that affect the cross-section of expected stock returns. We also note that although there is no direct hedging of beta risk, the dependent variable is very close to a zero beta portfolio.[14]

### 3.2. Summary Statistics

Panel A of Table 1 reports the *time series averages* of the cross-sectional means along with the time series averages of the cross-sectional standard deviations for all of the variables used in the regression as well as the analogously computed means and standard deviations on firm size, BE/ME, turnover, and institutional ownership. (All labels in the tables exclude the $t$ subscript for brevity.) Time series averages of value-weighted cross-sectional means also are reported.

The mean hedged return is close to zero, on the order of 0.1% equal weighted and 0.01% value weighted. Since this was a relatively good period for stocks, and since stocks tend to have positive returns, the means of the past return regressors, which are unhedged, are positive. This also explains why the 1- and 3-year consistent winners and losers dummies have averages that are

[14]Including market $\beta$, 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. Also, the hedged returns of the decile-based strategy we subsequently form from this regression have negligible exposure to the Fama-French factors.

above 10% and below 10%, respectively, with the deviation from 10% larger at the 3-year horizon.

The first four columns of Table 1 Panel B report the time series average of the equal- and value-weighted percentile rankings of stocks with various past return attributes. After classifying stocks each month into deciles for each of the three past-return horizons, the table shows the equal- and value-weighted averages of the stocks' size rank percentiles, BE/ME rank percentiles, turnover rank percentiles, and institutional ownership rank percentiles. It does this separately for stocks in each of three groupings: decile 1 (past losers), the middle eight past-return deciles, and decile 10 (past winners).

Note that, except for the 3-year horizon, stocks in deciles 1 and 10 tend to be of smaller size and book-to-market ratio, and at all horizons, have higher turnover than stocks in the middle eight deciles. It is not surprising that high volume (used to compute turnover) is associated with large absolute returns. The market cap and book-to-market ratio comparisons at the 3-year horizon are particularly affected by the fact that extreme long term returns can substantially alter a stock's market cap and its book-to-market ratio.

Panel B is useful for analyzing the type of firm in the portfolio strategies we will shortly analyze. For example, a typical long-short strategy based on past 1-year returns would buy stocks in decile 10 and short stocks in decile 1. If value weighting within the deciles, the long position would spend an average dollar on a stock with market cap percentile of 89.41, a BE/ME percentile of 44.49, a turnover percentile of 36.14, and an institutional ownership percentile of 67.30. The short positions in the strategy would spend an average dollar on a stock with market cap percentile of 70.41, a BE/ME percentile of 40.56, a turnover percentile of 62.97, and an institutional ownership percentile of 59.05. Differences in these percentiles point out the importance of subtracting out a benchmark return when studying the link between past and expected returns.

The two rightmost columns in Panel B report the time series average of the percentage of firms classified as consistent winners and consistent losers. Obviously, the decile 1 firms tend to have more consistent losers and the decile 10 firms tend to have more consistent winners. At the 1-month past return horizons, we are simply classifying whether the prior months' return was positive or negative. Hence, the percentages for "consistent" winners and losers sum to one.

### 3.3. Results from Fama-MacBeth Regressions

Table 2 reports the time-series average, from August, 1996 to July, 1995,[15] of the monthly coefficients from the cross-sectional regression in equation (1) along with Fama and MacBeth (1973) time-series $t$-statistics. The column labels identify whether the coefficients were averaged over all months, Januaries only, February through November only, or December only. The rows in Table 2 correspond to regressors. The three return rows, labeled $r_{-1:-1}$, $r_{-12:-2}$, and $r_{-36:-13}$, document a strong 1-month reversal effect, a weaker 1-year momentum effect, and a still weaker 3-year reversal effect, respectively, both when averaging the coefficients over all months and when averaging only the February to November coefficients. All of these effects are statistically significant. The three loser return coefficients are all of the same sign as the return coefficients, and statistically significant. This suggests that the effects of return persistence and reversals are exacerbated for negative past returns. Again, this is true for all months as well as February through November.

The seasonal pattern in Table 2 is particularly interesting, with both January return coefficients being negative for the 1-year variables. Jegadeesh and Titman (1993) identify positive profits for momentum strategies in every month except January, for which they document significant negative profits, and find stronger momentum profits in April, November, and December. They 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 (as well as control for 1-month return effects in the regression), the seasonal patterns observed here are not susceptible to this bid-ask bounce, yet exhibit the same pattern. Moreover, Jegadeesh and Titman (1993) do not separate out the seasonal effects of winners and losers. As Table 2 shows, the asymmetries between winner and loser return effects are quite important, and help to assess the degree to which other explanations, such as tax loss trading, account for the relation between past returns and expected returns, as we will see shortly.[16]

[15] 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. We end the estimation in July, 1995, reflecting the most recent data in the first draft of this paper. At the suggestion of an anonymous referee, we reserved the August, 1995 to December, 1999 period for out-of-sample tests.

[16] Grundy and Martin (2001) also document a significant negative momentum effect in January for the 1-year strategy, but do not examine the winner-loser asymmetry, analyze end-of-year returns, or attempt to link these phenomena to tax-loss trading.

It is interesting to speculate about whether the seasonal pattern in the coefficients reported in Table 2 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 2 documents a significant December persistence effect for both 1- and 3-year losing stocks. If the market for such stocks is particularly illiquid at the end of December, then 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 sums of the coefficients on the pair $r_{-12:-2}$ and $r^L_{-12:-2}$ and on the pair $r_{-36:-13}$, $r^L_{-36:-13}$, 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 the coefficient on the past winning returns over both the 1- and 3-year horizons, given in the rows for $r_{-12:-2}$ and $r_{-36:-13}$, are largest in December (with a positive coefficient rather than the normally negative coefficient, as noted above, for the long-term past return horizon).

Table 2 also contains evidence that is consistent with the conjecture that the turn of the year coincides with a particularly illiquid market, especially for past losers. The coefficients on both $r_{-1:-1}$ and $r^L_{-1:-1}$, which may be due to a liquidity effect, are most negative in January and slightly more negative than usual in December, but exhibit fairly similar magnitudes across the other months.

The prevailing wisdom, since DeBondt and Thaler (1985) and Chopra, Lakonishok, and Ritter (1992), is that the 3-year reversal is primarily driven by extreme losers. This is certainly true for January, (as DeBondt and Thaler (1985) and Chopra, Lakonishok, and Ritter (1992) also observed), as the January coefficient on $r_{-36:-13}$ is insignificant, indicating the absence of a 3-year winner effect on January returns. However, this hypothesis does not apply the rest of the year.

From February through November there is no difference in the impact of past 3-year positive and past 3-year negative returns, as evidenced by the insignificant coefficient on $r^L_{-36:-13}$. In addition, the sum of the December 3-year return coefficient and the loser return coefficient is not only positive, indicating *persistence* rather than reversals, but it is about eight times the size of the return coefficient (the impact of the positive returns) in December. As discussed later, the positive 3-year losers coefficient in December is consistent with year-end tax loss selling.

Finally, all 12 consistent winners coefficients in Table 2 are positive and most are statistically significant. This indicates that for all three horizons and all three seasonal subperiods, as well as the overall sample, the consistent winners outperform other stocks, ceteris paribus. At the 1-year horizon, the marginal impact of being a consistent winner is 46 basis points per month. Consistent losers have little impact on returns, suggesting that the impact of winner consistency is not due to the lower volatility associated with consistency, which would have an opposite effect and would apply to both losers and winners; rather, it reflects a more complex past returns effect.

### 3.4. The Relation Between Past Return Horizons

If the 1-year past returns effect determines the 3-year past returns effect, then intermediate horizon momentum is probably an overreaction to past news. This would considerably limit the set of valid theories that could explain these phenomena. Much of the literature claims there is a direct link between the effects of various past return horizons. For instance, Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) model an explicit link between intermediate-term momentum and long-term reversals based on various irrational investor cognitive biases. In addition, others have suggested such a link is present in the data.[17] By analyzing non-overlapping past return regressors and using hedged returns for our dependent variable, we can provide some additional evidence on this possible link. The non-overlapping returns make interpretation of the coefficients quite simple – they represent the marginal effects of the variable controlling for the other past return effects.

First, the fact that each past return horizon variable shows up significantly in our cross-sectional regressions suggests that at least part of these effects are independent from one another. Second, in

[17] See, for example, Hong, Lim, and Stein (2000) and Lee and Swaminathan (2000). Jegadeesh and Titman (2001), despite showing that profits for momentum dissipate by the year five horizon, are quite cautious in their interpretation, noting that horizon length, time period studied, and benchmarking of returns plays an important role in the inference about the linkage.

unreported results from a previous draft, we ran separate regressions for each past return horizon and found the coefficients to be almost identical to those from the full regression of Table 2. This suggests significant independence among the various horizons. Finally, the fact that the long-term reversals are almost exclusively driven by long-term losers in January, yet momentum is prevalent throughout the calendar year, also suggests that at least part of these past return horizon effects may be unrelated. This is not to say that there is not a significant component of long-term reversals that could be related to intermediate horizon momentum, but there does appear to be more independence between these effects than some prior research has suggested.[18]

# 4. The Economic Significance of the Past-Expected Return Relation

To examine the economic importance of the relation between past and expected stock returns, we form trading strategies based on past returns and the insights from the previous regressions. We analyze the profitability of these strategies both in and out of sample, and attempt to gauge the amount of trading and transaction costs incurred by the strategies.

## 4.1. Trading Strategies Based on Stock Ranks Generated by the Fama-MacBeth Regressions

Table 2's regressions provide an investor with a tool to formulate an investment strategy. We use the predicted returns from the Fama-MacBeth regressions of Table 2 to rank stocks and form decile portfolios with decile 10 containing stocks with the highest predicted returns. Rankings are determined by the beginning-of-month regressor values for the corresponding stocks, and use average coefficients from the appropriate sample of months (as discussed below) to weight the regressor values. Decile portfolios either value weight the stocks within each decile rank or equal weight them.

Most of our analysis is based on the spread between the hedged returns of decile portfolios 10 and 1. The strategy that creates such a spread is similar to strategies employed by many market neutral hedge funds: buying the stocks above some rank and shorting those below a particular rank, with a modest amount of hedging to adjust for any imbalance in the risk exposures of the

[18] Evidence in Chan, Jegadeesh, and Lakonishok (1996) and Jegadeesh and Titman (2001) further supports our viewpoint.

long and short positions.[19] Aside from the practical import of such analysis, backtesting the profitability and risk of a strategy based on Table 2's regression also is interesting for research reasons. First, it provides a measure of the economic importance of the relation between past and expected returns that regression coefficients (except for those on dummy variables) cannot provide.[20] Second, it provides a check on whether the functional form of the regression is sensible. Lack of a consistent monotonic pattern in the profitability of each decile portfolio might imply that the regression specification was driven by outliers. Third, it generates a parsimonious comparison of the economic importance of each horizon or of horizons in combination with one another. For example, if one believed that market microstructure effects were behind the significance of the 1-month past return coefficients in Table 2, it would still be appropriate to employ a ranking system from Table 2's coefficients on the remaining regressors. Similarly, if one wanted to assess whether a strategy based solely on the 1-year momentum effect was economically important, forcing all but the four slope coefficients associated with the 1-year horizon to zero would be appropriate to analyze profits. Finally, analyzing the spread between decile portfolios 10 and 1 for subsamples of stocks based on various attributes is a simple way to assess whether the economic relations uncovered apply more to certain sectors of the stock market.

### 4.2. The Profitability and Risk of Trading Strategies Associated with the Stock Ranking System

Panel A of Table 3 reports in-sample results for the average monthly benchmark-adjusted returns along with their annualized standard deviations of each corresponding decile portfolio (both equal- and value-weighted). The deciles in Table 3 Panel A are obtained using three sets of coefficients, which differ according to the three seasons. Table 3 Panel A portrays the average returns of a trading strategy that uses the January coefficients from Table 2 for January rankings, the February to November coefficients for ranking stocks from February through November, and the December coefficients for ranking stocks in December. The first two rows of Table 3 Panel A report, respec-

[19]It would also be possible to form a portfolio by weighting stocks in the ex-post mean-variance optimal fashion using ranks or predicted returns, along with their estimated standard deviations and covariances. However, absent extreme confidence that the coefficients were estimated precisely, it is unlikely that the "mean-variance optimized" strategy would dominate a simpler strategy out of sample.

[20]As Fama (1976) notes, each coefficient from a Fama-MacBeth regression is the return to the minimum variance portfolio with (i) weights that sum to zero, (ii) weighted characteristic on its corresponding regressor that sums to one, and (iii) weighted characteristics on the other regressors that sum to zero. However, the scale of each portfolio (i.e., dollars long and short) varies across regressors, making economic comparisons difficult.

tively, the average hedged returns and standard deviations of hedged returns of value-weighted decile portfolios formed from this dynamic trading strategy. The second two rows represent corresponding returns and standard deviations for monthly rebalanced equal-weighted portfolios.

We can see from the first and third rows of Panel A that the deciles are strictly monotonic. In comparison with their benchmarks, the decile 1 portfolio loses 47 basis points per month on average when value weighted, and loses 65 basis points per month on average when equal weighted. Relative to its benchmark, the decile 10 portfolio earns 92 basis points per month on average when value-weighted and 215 basis points per month on average when equal weighted. Hence, controlling for size, book-to-market, and industry, the best-ranked value-weighted portfolio outperforms the worst-ranked value-weighted portfolio by 139 basis points per month, and by 280 basis points per month when deciles 10 and 1 represent equal-weighted portfolios. The annualized standard deviations of the hedged returns of the ten decile portfolios is slightly U-shaped, both for the value-weighted and equal-weighted decile portfolios, but there is more volatility in the portfolios predicted to have the highest hedged returns than those with the lowest hedged returns. For example, the value-weighted decile 10 portfolio, with a benchmark-adjusted return volatility of 11% per year, is notably more risky than the other nine value-weighted decile portfolios.

The 139 basis points per month spread between value-weighted decile portfolios 10 and 1 in the first row of Panel A can partly be attributed to market microstructure effects. In particular, the past 1-month return may be negatively related to the current month return because of bid-ask bounce and related liquidity effects. To analyze this issue, Table 3 Panel B reports decile portfolio performance using a scoring system with coefficients identical to those in 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 value-weighted decile portfolios generated by the market microstructure-free regressors are still rather remarkable. At 111 basis points per month, the spread between value-weighted decile portfolios 10 and 1 is of similar magnitude to the spread in Panel A. The standard deviation pattern is also similar. As before, decile 10's benchmark-adjusted return volatility, at 10% per year, has the highest standard deviation of all decile portfolios.

The large coefficients on the 1-month reversal in Table 2 make the similarity between the (possibly market microstructure tainted) results of Panel A and the (microstructure free) results of Panel B somewhat surprising. We believe that the 25% difference between the 10-1 spreads in the first rows of Panels A and B of Table 3 probably is small because value-weighting within the decile ranks lessens the impact of contaminating market microstructure effects. Equal-weighting within the decile ranks (third rows of the two panels) generates an enormous 280 basis point spread between Portfolios 10 and 1 in Panel A. This is about 55% larger than the comparable 168 basis point spread for the equal-weighted portfolios in Panel B.

To assess the relative economic importance of the 1- and 3-year horizons, Panels C and D of Table 3 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 decile portfolios. The remaining coefficient estimates from the regression of Table 2 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, whether they are value- or equal-weighted.

A comparison of Panels C and D indicates that the past 1-year horizon, which generates a momentum strategy in all but January, has the stronger effect with a spread of 71 basis points per month between value-weighted deciles 10 and 1. The 17 basis point spread for the pure 3-year horizon strategy, when value-weighting, is only about one-fourth the size of the 1-year strategy's profitability. This may be because the 3-year reversal effect is concentrated in the extremes, and largely applies to small-cap stocks. Equal weighting within the deciles generates a 59 basis point spread between deciles 10 and 1 in Panel D. However, momentum is also a stronger economic effect among small stocks. Equally weighting the stocks within the deciles of Panel C also generates a much larger spread between deciles 10 and 1 – in this case 160 basis points. This suggests that despite the spread moderation induced by value weighting, the past one year has a stronger effect on expected stock returns than the past three years.

The standard deviations in Panel C are larger for the extreme decile portfolios with decile 10 exhibiting the greatest riskiness: an 8.7% per year standard deviation when value-weighted and an 8.4% standard deviation when equal-weighted. In Panel D, the hedged returns of decile 10, which, except for December, contains stocks with the most negative 3-year returns, exhibit volatility of 9.3% per year when value-weighted and 8.7% when equal-weighted.

An investor, concerned about liquidity, may wish to avoid stocks with low-priced shares. While we intend to address this issue later in the paper, we note that restricting the ranking to the universe of stocks with prices above five dollars per share lowers volatility, has little effect on the spreads observed in Panels B through D, nor does it greatly affect the value-weighted spread in Panel A. The equal-weighted spread in Panel A is substantially lower at 161 basis points per month.

This is expected as the bid-ask bounce and other liquidity effects that may be associated with the 1-month reversal are probably far larger for low-priced stocks.

### 4.3. The Importance of Past Winner Consistency from February through November

The results in Panels C and D of Table 3, and perhaps in Panels A and B as well, depend to some extent on the pattern of past returns within a horizon. In particular, being a consistent winner seems to enhance profitability. This is in part due to decile 10 effects for the 1-year strategy. For the one-year past return horizon, stocks with fewer than 8 positive returns over the 11-month horizon comprise 19.83% of the value-weighted returns for decile 10 (36.39% of the equal-weighted decile 10 portfolio). They are almost the entire sample of the stocks in decile 1. For the value-weighted portfolios, from February through November, there is no profitability to the 1-year strategy with these inconsistent stocks. Despite having a high predicted return, the inconsistent stocks within the decile 10 portfolio earn 22 basis points *less* than their benchmark on a value-weighted basis and are essentially indistinguishable from the stocks in the decile 1 portfolio. From February through November, the 1-year inconsistent decile 10 stocks beat their benchmark by a mere 20 basis points per month when equally-weighted. By contrast, a strategy of buying the 1-year consistent winners in decile 10 and shorting the remainder of the decile 10 portfolio, value-weighting each component, earns 53 basis points per month from February through November, almost as much as the strategy of buying value-weighted decile 10 and shorting value-weighted decile 1. A similar spread exists between consistent and inconsistent stocks for equal-weighted decile 10.[21]

### 4.4. Turnover for Trading Strategies and Transaction Costs

An investor trying to exploit the strategies described above would need to account for trading costs in deciding whether to pursue these strategies. Such an investor might also modify the strategies in Table 3 to reduce trading costs. For example, the results in Table 3 Panel A partly rank stocks based on the prior month's return. Since the top winning and losing stocks in a given month rarely are the top winning and losing stocks in the subsequent month, any strategy that heavily weights the past 1-month return to rank stocks is likely to turn over almost the entire portfolio each month. Moreover, the profits reported from such a strategy may be spurious to the extent

[21]The same lesson applies to the pure 3-year strategy, although here, the strategy was not profitable outside of January to begin with.

that they are due to liquidity or market microstructure effects.

Similarly, an investor concerned about trading costs would want to avoid or downweight stocks with particularly high trading costs, notably stocks with low prices and small market capitalizations. Grundy and Martin (2001) expressed concern that trading costs, as estimated by Keim and Madhavan (1997), may jeopardize the profitability of a momentum strategy. This concern may apply to a portfolio strategy that is formulated without regard to turnover and transaction costs. The portfolio studied by Grundy and Martin (2001) is equal-weighted and allows investment in low-priced stocks. This generates excessive trading costs both because of its emphasis on small-cap low-priced stocks and because the rebalancing inherent in an equal-weighted portfolio strategy generates additional turnover.

An investor, concerned about transaction costs, would be more interested in value-weighted results than equal-weighted results and in stocks with share prices that are not too low. In our case, restricting the portfolios formed in Table 3 to above \$5 stocks is fairly innocuous; if we repeat the analysis of Tables 2 and 3, but focus exclusively on stocks with prices above \$5 at the beginning of the month, the average spread between value-weighted deciles 10 and 1 in Panel B declines from 111 basis points per month to 100 basis points per month. In Panel C, it actually increases: from 71 basis points per month when using all stocks to 77 basis points per month when using just the stocks with share prices exceeding \$5.

The trading costs of the above \$5 per share value-weighted Panel B strategy, and modest variations of it, are still substantial, but still far smaller than the sizable profits earned before transaction costs. This strategy, as before, forces the coefficients on the past 1-month regressors to zero, and ranks stocks based on variables constructed from the returns of both the past one year and past three years. While 100 basis points per month is impressive, the turnover of the strategy is large. In our final year, 1999, which was particularly volatile, turnover (dollar buys plus dollar sells per dollar invested) on the long side of the strategy (decile 10) is 38.86% per month, while that on the short side (decile 1) is 63.75% per month. This is about 1/3 less turnover than the turnover in Grundy and Martin's pure equal-weighted momentum strategy and is about 1/3 less profitable as well.

However, there is a huge difference in the trading costs of the strategy per trade. Table 1 Panel B indicates that even without the minimum \$5 per share restriction, our value-weighted portfolio strategy spends most of its dollars on large cap stocks. The typical dollar invested in a long or a short position is in a stock that is between the 80th and 85th percentile in market capitalization. Cutting out the below $5 per share stocks raises both the long and the short positions to the 86th percentile of market capitalization. These stocks have substantially lower trading costs than the average stock. Moreover, the information we use in formulating the Panel B strategy is at least 1-month old. Hence, there is no urgency to the trades, allowing such trades to be split into smaller sizes and executed over a period of days or perhaps even weeks.

A recent study by a practitioner expert, Wayne Wagner, (www.plexusgroup.com) has estimated that for large cap stocks, a cost of about 0.32% reflects market impact and brokerage commission for trades, while 0.55% covers a smaller cap trade. If trading costs are $x\%$ of each dollar spent or received, trading costs reduce returns by $102.61x$ basis points per month. Hence, Wagner's large cap cost estimate reduces the pre-trade profitability of the strategy by about 1/3 while the small cap cost estimate reduces it by approximately one-half. As value-weighting places more emphasis on the larger cap stocks, these costs would not be sufficient to wipe out the trading strategy's profits. Since the introduction of decimalization and Internet commissions were not accounted for in this study, these costs may now be even lower.

Based on the formula above, trading costs of about 1% are approximately the breakeven costs for this strategy. However, even for earlier periods, when institutional brokerage commissions accounted for 20 to 30 basis points of trading costs, depending on share price, the findings in Keim and Madhavan (1997) support the notion that trading costs would be far less than 100 basis points for a value-weighted strategy restricted to stocks with share prices above $5 per share.[22] Keim and Madhavan (1997) have suggested that trading costs for institutions depend on both the trade size, which is largely related to the need for immediacy, market capitalization, exchange, and whether the trade is a buy or a sell. For buys and sells that consist of less than 0.0775% of the outstanding market capitalization of a stock,[23] one-way trading costs in the two largest size quintiles ranged from $-95$ to 67 basis points. The Keim and Madhavan (1997) worst case scenario leaves about 400 basis points in profit for the investor here.

Even our lowest trading cost estimates may overstate the friction associated with trading costs

[22]Some of our stocks end up below $5 per share and thus might experience higher trading costs. However, the bias induced by this is probably offset by our requirement that all positions in below $5 stocks be liquidated, even if the regression-based ranking suggests that they should remain in the portfolio. In addition, value weighting makes the impact of both of these effects negligible.

[23]This excludes only the largest trade size category studied by Keim and Madhavan (1997).

for these kinds of strategies. For example, a significant component of the turnover in the strategy we use comes from shorting decile 1. Short sales of the stocks in decile 1, however, are not necessary to earn substantial profits relative to the benchmark. The profits for the long side of the strategy (decile 10) net of benchmark portfolio returns are 66 basis points per month. Hence, even if short sales restrictions were costly (and D'Avolio (2001) and Reed (2001) find that for most stocks they are not), there still are substantial rents that can be earned from a long strategy that beats a similar book-to-market, size, and industry-matched benchmark. The 66 basis points per month abnormal return from buying decile 10 would only be wiped out by one-way transaction costs of at least 1.70%, which may be almost an order of magnitude too high for value-weighted portfolios.

Variations of the strategy that attempt to reduce turnover have similar breakeven one-way trading costs of about 100 basis points. For example, if we employ the same strategy but avoid trading between February through November, decile portfolio 10 outperforms decile portfolio 1 by 28 basis points per month rather than 100 basis points per month. However, average turnover on the long side (decile 10) declines to 11.36% per month and average turnover on the short side (decile 1) declines to 20.88%. The combined 32.24% turnover eliminates trading profits if one-way trading costs exceed 0.85%. This trading cost is unlikely given the value-weighting within the deciles. Similarly, if we trade only once (at the midway point, June 30) from February through November, but otherwise undertake the same strategy, decile portfolio 10 outperforms decile portfolio 1 by 45 basis points per month while the sum of the average turnover rates from both the long and short sides of the strategy is 43.76%. Thus, 1% approximately represents breakeven one-way trading costs here.

Finally, we point out that even if trading costs eliminated the profitability of these strategies entirely (and we do not believe they do), you still want to tilt your portfolio toward stocks based on their past returns, or ceteris paribus, choose stocks with "more favorable" past return patterns. The marginal transaction cost is zero in this case. Alternatively, professional investors have software packages that maximize objective functions that include penalties for the frictions associated with trading in stocks of differing liquidity classes. It is conceivable that these packages could reduce frictions from trading costs substantially more than the "naive" trading rules studied here.

## 5. The Influence of Past Returns Across Seasons, Out of Sample, and within Various Sectors of the Economy

This section examines whether the trading strategy profitability varies across seasons and across different sectors of the stock market. Such information might be useful to enhance the profitability of a trading strategy that is based on past return patterns. It also may shed light on the underlying cause of the past return relation with the cross-section of expected returns.

### 5.1. Seasonalities in the Economic Importance of Each of the Past Price Variables

Panel A of Table 4 reports in- and out-of-sample averages of the spreads between the hedged returns of value-weighted decile portfolios 10 and 1 along with their annualized standard deviations. The left half of Panel A presents in-sample results from August, 1966 to July, 1995. The first row of the left hand side of Panel A summarizes the same information in Table 3, reporting the difference between deciles 10 and 1. Each column corresponds to a respective panel in Table 3. In contrast to Table 3, the left half of Table 4 Panel A also decomposes these average spreads and standard deviations into January-only, February to November-only, and December-only statistics.

January and December are the most profitable times for the strategies. January accounts for about 1/3 to 1/6 of profits for the strategies employed in the first three columns and is largely responsible for any profitability that the 3-year strategy in the fourth column possesses. Although the latter result is partly an artifact of value-weighting within the deciles, there are no profits from DeBondt and Thaler's 3-year reversal outside of January. (In December, the 3-year strategy presented here becomes a momentum strategy.) 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 only minimally enhance the exceptional performance of the value-weighted strategies. We also cannot attribute the performance of these strategies to a small growth firm effect, in that the returns are hedged against size, value, and other factors and are based on value weighting within the decile portfolios.

### 5.2. Out-of-Sample Results

Perhaps it is not surprising that the profitability of the trading strategies in the left half of Panel A 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, the specification for the scoring system employs variables known to be related to average returns from previous studies. 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.[24]

The right half of Table 4 investigates whether the technical trading strategies' profits are entirely due to chance fits of data that, in reality, are unpredictable. 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, the results obtained here would not hold on the five years of additional data that have become available since the prior draft of this paper formulated this trading strategy.

The right hand side of Panel A reports the same profitability information as its left hand side counterpart. It uses the same ranking strategy based on the same coefficients as that used on the left hand side. Despite the handicap of being entirely out of sample, the spread in the hedged returns of the value-weighted deciles is either about the same or is substantially larger than it was in sample. For example, the "all" strategy is about 64 basis points per month more profitable in the out-of-sample period, August, 1995 to December, 1999, as in the in-sample period. The strategy in the second column, which excludes the past 1-month regressors in forming portfolios, has 36 basis points less profit than its in-sample counterpart, but at 75 basis points per month, it is still a highly profitable value-weighed strategy. The 3-year strategy was unprofitable in sample but is highly profitable out of sample and the 1-year strategy is about as profitable out of sample as in sample. This suggests that the observed structural relation between past and future returns is relatively stable and is unlikely to be a product of data snooping.[25]

A similar comparison applies if we exclude stocks with low share prices. Panel B reports the same in- and out-of-sample profitability numbers as Panel A, but excludes all stocks with beginning-of-month share prices below $5. Earlier, we noted that each strategy's profitability is barely affected by the exclusion of low-priced stocks, due to value-weighting within the deciles.

[24] 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.

[25] Jegadeesh and Titman (2001) also document that momentum strategies are equally profitable over the 1990 to 1998 time period as they were over their original sample period from 1963 to 1989, providing further out-of-sample evidence that diminishes data snooping concerns.

Thus, even though many stocks in the Panel A's strategy have low share prices, such stocks tend to receive little weight in the portfolio. When they are replaced with stocks possessing similar past return attributes, but larger share prices, the overall effect on the portfolio is negligible.

This finding holds up out of sample. The out-of-sample spread in the hedged returns of the value-weighted deciles is either about the same or is substantially larger than it was in sample. For example, the "all" strategy is about 44 basis points more profitable in the out-of-sample period, August, 1995 to December, 1999, as in the in-sample period when excluding low-priced stocks. The strategy in the second column, which excludes the past 1-month regressors in forming portfolios, generates about 29 basis points more profit than its in-sample counterpart. The 3-year strategy is more than twice as profitable and the 1-year strategy is about 50% more profitable out of sample.

### 5.3. Profitability Across Sectors of the Stock Market

We now analyze the profitability of the trading strategies across firms that differ by size, growth (proxied by book-to-market equity), turnover, and institutional ownership. 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 differently among stocks that differ along these and other dimensions.

Panel C of Table 4 repeats the exercise in Panel A, but employs subsamples based on firm size quintiles using NYSE breakpoints. 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 column, observe that a strategy generated by all coefficients except those associated with the past month earns 201 basis points per month through 1995 when applied to only the smallest quintile of stocks, but only 52 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 (1st column) only modestly enhances the profitability of the strategy. The effect of past 1-month returns (which may be tainted by microstructure effects) is clearly larger for the smallest quintile of stocks.

Except for the pure 3-year reversal strategy, the profits of which are largely driven by January to begin with, the increased spread between deciles 10 and 1 among the smallest quintile stocks (relative to the largest quintile) in the left hand side of Panel C is not driven by any one particular season. However, the greatest spread differences between the size groupings arise in December and January. Hence, the stronger influence of past returns on expected returns for small stocks documented by Hong, Lim, and Stein (2000) is at least partly driven by a strong year-end seasonal. Such seasonal patterns are difficult to explain with Hong, Lim, and Stein's (2000) slow information diffusion theory of these findings. The stronger December persistence and January bounceback among the smallest firms appears more 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 may be due to other factors, including slow information diffusion.

Restrictions to any subsample of stocks limits the range of past return attributes that can be achieved. However, the in-sample profitability of the small cap stocks is generally larger than that of the full set of stocks from Panel A. This is consistent with the technical trading strategy being more effective because of the small firm attribute rather than because the decile portfolios generated for the subsample do not contain sufficiently extreme past returns.

In the out-of-sample period on the right side of Panel C, small-cap stocks appear to relate to past returns differently than they did in the prior 30 years. However, given the higher volatility of these stocks and the brevity of the out-of-sample period, it is difficult to assess whether the change is simply a byproduct of sampling error, a structural change in the relation between past and expected returns, or evidence of data snooping bias. For example, the out-of-sample January numbers are negative for three of the four strategies, but there are only four Januaries with which to compute these profits. This is hardly compelling evidence that January reversals among small cap stocks have ceased to be the norm.

In addition to size, researchers have argued that a firm's growth prospects may affect the relationship it exhibits between its past and expected returns.[26] Panel D repeats the previous exercise employing subsamples based on book-to-market equity quintiles (a proxy for growth). To control for the potentially confounding effect of firm size, Panel D reports profits for strategies restricted to firms belonging to various size and BE/ME groupings. BE/ME quintiles are formed within the smallest and largest third of stocks. 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

[26] See, for example, Daniel, Hirshleifer, and Subrahmanyam (1998).

within the largest cap stocks are similar, but slightly stronger 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 more profitable among the lowest book-to-market quintile, and not because of December or January. This appears consistent with the conjecture in Daniel, Hirshleifer, and Subrahmanyam (1998) that anomalies (i.e., those associated with past returns) are likely to be stronger among firms that are "difficult to value" such as growth firms. However, it also is consistent with more extreme past return realizations arising within the growth sector of the small cap stock universe.

Panel E employs subsamples based on turnover, defined as the number of shares traded per day as a fraction of the number of shares outstanding, averaged over the prior 12 months. This share-normalized volume measure is employed by Lee and Swaminathan (2000), who show that it has a relatively low correlation with firm size. Lee and Swaminathan (2000) examine NYSE-AMEX traded stocks and find that momentum and subsequent 3-year reversals are stronger among stocks with high volume, mostly driven by the dismal performance of high volume losers. In a footnote, Lee and Swaminathan (2000) also report that they replicated their results with NASDAQ-NMS firms from 1983 to 1996 and that, for these firms, the predictive power of volume for future returns appeared even stronger.

Trading volume is not comparable between stocks listed on NASDAQ and those listed on either the NYSE or AMEX exchanges.[27] Therefore, we separately report results for NYSE/AMEX and NASDAQ stocks. The breakpoints for the volume quintiles are exchange specific. In general, the investment strategies we formulate generate higher returns among high volume stocks. Thus, at first glance, our findings are consistent with Lee and Swaminathan (2000). However, the added profitability among high volume NASDAQ stocks is due to performance at the turn of the year. Among NASDAQ firms, for instance, the profitability of 1-year momentum is enhanced by high turnover, but this is entirely due to January and December, consistent with year-end tax loss selling. In December, the high volume momentum stocks outperform the low volume momentum stocks. In January the reverse is true, but our 1-year strategy becomes a contrarian strategy at that point. Among NYSE-AMEX stocks, the 1-year strategy is more profitable on high volume than low volume stocks from February to November. While this may imply that other factors besides tax loss

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

selling may be contributing to these results, it would be difficult for such a theory to simultaneously explain why the reverse is true for NASDAQ stocks. Such a theory would also have to explain why, even among NYSE/AMEX stocks, the degree to which volume enhances profitability is so much higher in December. Note also that among both NYSE/AMEX (as with NASDAQ stocks), the high-volume 1-year strategy outperforms the low-volume strategy in January. Since the latter strategy is contrarian in January, a low volume momentum strategy should outperform a high-volume momentum strategy in January.

The salience of December and January to the enhanced profitability of the strategies among high volume stocks seems inconsistent with Lee and Swaminathan's (2000) behavioral story about volume and momentum, termed the momentum life cycle theory. This story, like most behavioral stories, should not exhibit seasonalities. While it is possible that some combination of tax loss selling and behavioral finance theory could account for the observed volume/profitability pattern, the empirical research used to justify these theories makes no attempt to take out a component of returns due to tax loss trading. If one does this, in many cases, no empirical anomaly remains. Our findings point to year end tax loss selling as a potential alternative to the mysterious role played by volume in the relation between past returns and expected returns.

To further investigate the role of tax motivated trading on these profits, we examine subsamples based on institutional ownership. If tax motivated trades drive the relation between past and future returns, then the profitability of our strategies should be strongest among firms with low institutional ownership, particularly in December and January. This is because individual investors are likely to be more concerned than institutions about capital gains taxes. To investigate this hypothesis, Panel F repeats the exercise in Panel D, employing quintiles based on the fraction of a firm's shares held by institutions, as reported by Standard & Poor's,[28] within the smallest and largest third of stocks.

For small cap stocks, for which tax motivated trades are likely to have the greatest impact on prices, low institutional ownership enhances the profitability of the strategies. This is especially true in January and December, a finding that is consistent with the results in Sias and Starks (1997).[29] However, within the largest quintile of stocks, institutional ownership does not appear to have a consistent effect, even for January and December.

[28] Due to data limitations, the analysis here is from 1981 on.

[29] They 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.

An alternative explanation for the contrasting findings is related to the observation by Grinblatt, Titman, and Wermers (1995) that mutual funds, which concentrate in large cap stocks, tend to follow momentum strategies. Thus, it is possible that large cap stocks with large institutional ownership have more mutual fund investment than the small cap stocks with large institutional investment. To the extent that momentum represents underreaction to news, the behavior of this institutional class may be reducing the rewards to momentum investing in the stocks favored by mutual funds. However, this alternative explanation for the negligible impact of institutional ownership on large cap stocks cannot account for the seasonalities observed.

## 6. Does Tax-Motivated Trading Impact the Relation Between Past and Expected Returns?

So far, we have hinted that the strong seasonal pattern in the past-expected return relationship may be driven by tax-motivated trades. Evidence on size, turnover, and institutional ownership was consistent with this conjecture. To test this more directly, we examine how tax regime shifts alter the profitability of our trading strategy.

We measure the profitability of our value-weighted trading strategy (excluding 1-month effects) for two subsamples – "high tax years," which are years or intervals of years at which the beginning year $t$ has a maximum short-term capital gains tax rate that is at least 20% higher than the average of the maximum rate in the two surrounding years, $t-1$ and $t+1$; and "low tax years", which are years or intervals of years at which the beginning year has a maximum short-term capital gains tax rate that is at least 20% lower than the average of the maximum rate in the two surrounding years. Years that do not fall into either of the 20% change categories share the same classification as the year immediately prior. By this rule, high tax years correspond to 1968-69, 1972-75, 1981, 1985-86, 1988-99 and low tax years are all other years in our sample. In determining whether a particular January belongs to a high or low tax year, we assign the respective January to the year of its adjacent December. For example, January 1982 is a high tax observation because 1981 is a high tax year.

To test whether differences across tax regimes affect strategy profitability, we ran a time-series regression of the spread between the hedged returns of value-weighted deciles 10 and 1, using the ranking system that excludes the past 1-month regressors, on dummy variables for high tax years, Januarys, Decembers, high-tax Januarys, and high-tax Decembers. In this regression, the intercept represents the strategy's average profitability in low-tax February-November months, and the coefficients on the five dummy variables represent the marginal effect on strategy profitability of various types of months. Table 5 Panel A reports the coefficients and $t$-statistics from this regression. The most striking aspect of the regression is that only the high tax January and high tax December coefficients are significant. The lack of statistically significant average profits from February to November and turn-of-the-year seasonals in low tax years is also rather surprising and heretofore unknown.

The insignificance of three of the five dummy coefficients in Panel A implies only that the marginal effect of the associated variables is insignificant. Profits earned in the months represented by the insignificant dummy variables could still significantly differ from zero. However, analyzing this issue directly, we find that only the high tax year profits significantly differ from zero. This is rather obvious in December, where the low-tax profits are only -27 basis points per month (obtained by subtracting the December coefficient from the constant). However, even the low tax year January profit of 162 basis points (the sum of the constant and the coefficient on the January dummy), although economically notable, does not significantly differ from zero when earned over only 12 Januarys ($t = 1.31$). Moreover, the average monthly profit over all months in the low tax regime, 37 basis points, is also insignificant ($t = 1.08$). By contrast, average February through November profits in high tax years are 75 basis points per month, which significantly differs from zero ($t = 2.63$). This high-tax-year profit increases by 362 basis points in the high-tax Januarys and by 451 basis points in the high-tax Decembers. Hence, not only do profits from the strategy substantially increase from insignificance to significance in high tax years, but there is a pronounced seasonality to the profits that is not present in the low tax years.

The pattern observed in Panel A is consistent with tax-loss selling as an important driver of the strategy's profitability. Even the significant profits from February through November of high tax years could be generated by a steadily increasing supply of losing stocks for sale that reaches a peak in December. However, if the profitability pattern across tax regimes is truly due to tax-loss selling, it should show up most strongly among the decile of losing stocks. Because we are excluding the past 1-month in formulating the strategy, this corresponds to decile 10 in December and to decile 1 in January. Moreover, this turn of the year pattern across tax regimes should exhibit enhanced profits for those stocks that are most likely to be held by taxable investors. These would be small cap stocks with low institutional ownership.

Panels B and C of Table 5 report the December and January hedged returns of losing stocks. Panel B reports the hedged December returns of the decile 1 portfolio within six subcategories of stocks and across the two tax regimes; Panel C reports the analogous January hedged returns of the decile 10 portfolios. The six subcategories consist of three matching category pairs: smallest and largest quintile of stocks, lowest and highest institutional ownership quintile within the smallest third of stocks, and lowest and highest institutional ownership quintile within the largest third of stocks. The results in these two panels are consistent with tax loss selling being an important driver of the temporal link between stock returns.

In Panel B, the decile 1 stocks (losers) exhibit negative hedged returns in high-tax Decembers. These hedged returns are substantially lower than the hedged returns in low-tax Decembers, across all categories. In Panel C, the decile 10 stocks have sizable positive hedged returns in high tax Januarys. In all but one case they exceed their low tax counterparts. The exception is a high-institutional ownership category which should not be particularly tax rate sensitive.

The tax hypothesis also seems to be consistent when comparing across categories. In Panel B, the high tax December hedged returns of decile 10 are negative for each category of stocks, but substantially more negative for the less taxable ownership category within each of the three pairings. In low tax Decembers, the more taxable ownership category in each of the three pairings has lower hedged returns, but many of the hedged returns are positive; and, among large cap stocks, institutional ownership only accounts for a three basis point difference in December profitability.

In Panel C, every category of stock ownership has positive decile 10 hedged returns. However, in both high and low tax Januarys, it is the taxable category within each of the two small cap pairings that has the more positive returns. Among large cap stocks, institutional ownership appears to have the reverse (although negligible) effect on profitability. Thus, it appears as if institutional ownership may not be related to tax loss selling among value-weighted portfolios of large cap stocks. This would not be surprising if the tax loss selling hypothesis accounts for our findings.

## 7. Summary and Conclusion

The literature on the relation between past and future returns is vast and crowded. While bits and pieces of what we investigate have been alluded to in this literature, no paper studies these issues synthetically. This has allowed us to advance the literature in several areas.

*Understanding Asymmetries.* For instance, researchers like Hong, Lim, and Stein (2000) and Lee and Swaminathan (2000) have asserted that portfolios of losing stocks subsequently underperform a portfolio of average performing stocks to a greater degree than winning stocks outperform average stocks. However, when the characteristics of average stocks differ dramatically from those of past winning and losing stocks (as we show in Table 1), the returns of stocks with the past returns in the middle grouping are not an appropriate benchmark for either past winning or past losing stocks. Our regression specification and use of hedged returns of stocks with expected values of zero under the null, provide cleaner ways to assess whether the short or the long side drives the abnormally large profit of technical trading strategies. Here, the hedged returns of the stocks predicted to have the highest (lowest) returns indicate whether the long (short) side of an investment strategy based on past returns is profitable and their magnitude quantifies the degree of profitability arising solely from past return variables. The asymmetries uncovered, especially when broken down by season, lead us to investigate tax loss trading as an important driver of the profitability of technical trading strategies.

*Relating Reversals to Tax Loss Trading.* DeBondt and Thaler (1985) and Chopra, Lakonishok, and Ritter (1992) show that contrarian strategies based on long-horizon groupings of stocks work best with losing stocks in January. Zarowin (1990) further argues that this is primarily a small-cap phenomenon. DeBondt and Thaler (1987) and Chopra, Lakonishok, and Ritter (1992) claim these reversals are not solely contained in January and are not due to tax-motivated trading. Rather, they argue that investor overreaction is the likely explanation. Conversely, Chan (1988) and Ball and Kothari (1989) argue that rational time-variation in expected returns can explain these reversals. Fama and French (1996) show that these contrarian profits are driven by small, distressed firms, and that they disappear once the premia associated with their factors are accounted for. Our analysis contributes to the literature here by separating long-term reversals from other past return effects and uses hedged returns to account for confounding return premia, providing a more powerful test. We find that the long-term reversal effect exists largely for losing stocks in January, and that this January return is not captured by other return premia. Hence, our results appear inconsistent with either overreaction or a risk story, and point to seasonal explanations such as tax loss selling.

*Exploring the Link Between Momentum and Reversals.* Much of the literature claims or explicitly models a direct relation between the effects of various past return horizons. For instance, Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) all provide models linking intermediate-term momentum with long-term reversals under various theories of irrational investor behavior. Hong, Lim, and Stein (2000), Lee and Swaminathan (2000), and Jegadeesh and Titman (2001) claim that such a link exists in the data. By analyzing non-overlapping return horizons simultaneously, and carefully controlling for confounding return premia, our study provides a cleaner test of the potential link between momentum and reversals. We find, however, that at least part of these effects evolve independently. The fact that the long-term reversal effect appears only in January, yet significant momentum exists outside of January, appears inconsistent with these effects resulting from the same investor behavior. If there is a link, it may driven by the December/January tax-loss selling link, which seems inconsistent with behavioral theories of overconfidence or the momentum life cycle. Certainly, future theory should consider the relevance and importance of these seasonal effects before attempting to link them.

*Testing Behavioral Theories of Momentum and Reversals.* Our examination of the relation between past and expected returns across various segments of the market may also shed light on many potential explanations offered for these anomalies. Hong, Lim, and Stein (2000) and Lee and Swaminathan (2000) show that the intermediate momentum effect is stronger among smaller stocks and more frequently traded stocks, respectively. Both of these findings stem from greater persistence among small, high turnover losers. While both papers promulgate a behavioral explanation for their results, we find that at least part of the effect of size and turnover can be attributed to a turn of the year seasonal that seems more consistent with tax loss selling than a behavioral bias story. Moreover, we examine the impact of size and turnover on the past/expected return relation over all horizons (short, intermediate, and long-term). In addition to size and turnover, some of the relation between past and expected returns across book-to-market equity categories may be consistent with the model of Daniel, Hirshleifer, and Subrahmanyam (1998), who argue that more "difficult to value" firms such as growth firms should exhibit stronger momentum and more pronounced long-term reversals. Finally, examining the influence of past returns across institutional ownership structures helps determine whether firms predominantly held by institutions or individuals exhibit stronger past return effects. Lakonishok, Shleifer, Thaler, and Vishny (1991) and Barberis and Shleifer (2001) argue that institutions will exacerbate these effects due to window dressing or positive feedback trading. On the other hand, the influence of past returns may be more potent for firms with large individual investor ownership clienteles whose trades may be motivated by tax-loss selling (e.g., Sias and Starks (1997)). Our results indicate that low institutional ownership generates stronger past return effects, thus supporting the tax trading hypothesis. Analyzing the effect of past returns across these segments of the economy (some revisited, some novel) aids in determining the source of these anomalies for future theory.

*Exploring the Role of Tax Loss Trading in Depth.* Our study of how tax regimes affect the relation between past and expected returns also improves our understanding of these phenomena. In addition, it tests the import of tax motivated trading on asset prices. Although numerous studies have analyzed the tax-loss selling hypothesis, most focus on stock returns in January, and few examine variations in the tax code. A recent exception is a paper by Poterba and Weisbenner (2000), which analyzes how returns in the first few trading days of January 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. In contrast to their study, we examine changes in the maximum capital gains tax rate and analyze *both December and* January returns. More importantly, our focus is entirely different: We analyze how tax regimes affect the profitability of technical trading strategies, whether they are focused on all stocks or subgroups of stocks, like the small cap and low institutional holding categories, that are expected to be particularly susceptible to tax loss trading. A by-product of this analysis is a better understanding of how tax-loss trading affects stock prices, which is the focus of Poterba and Weisbenner (2000). We find statistically significant profits from technical trading strategies are present only in high tax regimes, including the strong seasonal effects. Moreover, the subcategories of stocks on which these technical trading strategies work best are those most susceptible to tax loss trading.

*Identifying New Variables that Determine the Cross-Section of Expected Returns.* Several papers have attempted to incorporate past returns into a model of the cross-section of expected returns using a relatively simple benchmark. 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. 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. None of these papers, however, address whether the consistency of past returns matters or how seasonal effects alter the influence of past returns. Given the complexity in the relation between past and expected returns, this paper provides a much more comprehensive, yet parsimonious, characterization of the cross-section, offering a more accurate and more robust method for accounting for the influence of past returns on expected returns. The simultaneous analysis of all past return horizons and seasonal patterns, the impact of past return consistency and tax regimes, the out-of-sample performance of trading strategies, and the economic evaluation of trading strategy profits that account for trading costs, are all novel innovations to this literature.

*Developing an Understanding of the Role of Data Snooping, Trading Costs, and Market Microstructure Effects.* Finally, our use of non-overlapping returns, value-weighted strategies, and comparisons of profitability across strategies and seasons allows us to assess the importance of market microstructure effects and transactions costs on the profitability of technical trading strategies. For value-weighted strategies, profits are still large after trading costs are accounted for and after eliminating the microstructure-related influence of the past month. We also found that profitability did not decline in the out of sample period studied. This suggests that the profitability uncovered here reflects some underlying regularity in stock prices rather than a byproduct of data snooping, and does not appear to have persisted because of substantial trading cost frictions.

Our synthetic approach provides insights into previous findings about the temporal relationship of returns and uncovers new evidence and additional complexities of this relation. The new set of stylized facts we document suggests that the relationship between past returns and expected returns is largely inconsistent with current theories of momentum and reversals in behavioral finance models. The additional complexities that influence the relation between past and expected returns, including the sign and consistency of past returns as well as seasonal effects, need to be accounted for in future theory and empirical tests of these theories in progressing toward an understanding of this relationship.

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Table 1:
Summary Statistics of Past Return Variables and Firm Characteristics

Panel A reports time-series averages of the equal- and value-weighted cross-sectional means and standard deviations of twelve variables used in a cross-sectional regression and four firm-characteristic variables used to later subdivide the sample. Monthly data from August, 1966 to July, 1995 are used. Hedged returns are adjusted for size, BE/ME, and industry effects by subtracting the same-month returns of a hedge portfolio of similar size, book-to-market, and industry attributes. Regressors include past return variables of the stock from the previous month ($r_{-1:-1}$), previous year (cumulative return from month $t-12$ to month $t-2$, $r_{-12:-2}$), and previous three years (cumulative return from month $t-36$ to month $t-13$, $r_{-36:-13}$); interaction variables between each past return and a dummy indicating if that past return was negative, $r^L_{-t2:-t1}(j) = min(0, r_{-t2:-t1}(j))$; and dummies for whether the stock was a consistent winner ($D^{CW}_{-t2:-t1}$) or loser ($D^{CL}_{-t2:-t1}$) over the $t-t2 : t-t1$ horizon. If the stock had a positive return last month, $D^{CW}_{-1:-1} = 1$; $D^{CW}_{-12:-2} = 1$ (or ($D^{CL}_{-12:-2} = 1$)) if the stock exhibited positive (negative) returns in at least 8 of the 1-year horizon's 11 months; $D^{CW}_{-36:-13} = 1$ (or $D^{CL}_{-36:-13} = 1$) if the stock exhibited positive (negative) returns in at least 15 of the 3-year horizon's 24 months. Also reported are summary statistics on size (market capitalization), book-to-market equity (BE/ME), trading volume (turnover), and percentage of outstanding shares that are institutionally owned. Panel B reports summary statistics on three sets of decile portfolios formed from past 1-month, past 1-year, and past 3-year returns, respectively. The percentage of stocks in each decile that are classified as consistent winners and losers are reported along with the percentile rank of the average stock in each decile with respect to size, BE/ME, turnover, and institutional ownership. These statistics are computed every month for each decile, and the time-series average of these measures are reported.

| | *Time-Series Average of Cross-Sectional Statistics* | | |
|---|---|---|---|
| | **Panel A: Regression Variables** | | |
| | Equal Weighted Mean | Standard Deviation | Value Weighted Mean |
| **Dependent Variable** | | | |
| Hedged Return | 0.0012 | 0.1337 | 0.0001 |
| **Past Return Variables** | | | |
| $r_{-1:-1}$ | 0.0114 | 0.1333 | 0.0116 |
| $r^L_{-1:-1}$ | -0.0404 | 0.0649 | -0.0264 |
| $D^{CW}_{-1:-1}$ | 0.4950 | 0.4723 | 0.5472 |
| $r_{-12:-2}$ | 0.1405 | 0.4837 | 0.1921 |
| $r^L_{-12:-2}$ | -0.1083 | 0.1679 | -0.0438 |
| $D^{CW}_{-12:-2}$ | 0.1353 | 0.3201 | 0.2179 |
| $D^{CL}_{-12:-2}$ | 0.0724 | 0.2436 | 0.0349 |
| $r_{-36:-13}$ | 0.3764 | 0.9482 | 0.5393 |
| $r^L_{-36:-13}$ | -0.1085 | 0.1900 | -0.0285 |
| $D^{CW}_{-36:-13}$ | 0.1849 | 0.3808 | 0.3680 |
| $D^{CL}_{-36:-13}$ | 0.0611 | 0.2308 | 0.0228 |
| **Firm Characteristics** | | | |
| Size ($mill.) | $45.433 | $212.028 | $1,129.576 |
| BE/ME | 0.9393 | 0.7157 | 0.7270 |
| Volume (turnover)† | 0.6176 | 3.4147 | 0.1380 |
| Institutional Ownership‡ | 25.21% | 20.99% | 44.48% |

| | | %Size rank | %BE/ME rank | %Turnover† rank | %Inst. Own.‡ rank | %CW | %CL |
|---|---|---|---|---|---|---|---|
| | | *Time-Series Average of Cross-Sectional Statistics* | | | | | |
| | | **Panel B: Decile Portfolios** | | | | | |
| | **Past 1-Month Returns** | | | | | | |
| | *Equal Weighted* | | | | | | |
| *low* | Decile 1 | 36.98% | 43.89% | 69.26% | 41.58% | 0.00% | 100.00% |
| | Deciles 2-9 | 52.82% | 50.99% | 45.95% | 51.68% | 44.49% | 55.51% |
| *high* | Decile 10 | 40.77% | 48.23% | 63.05% | 45.17% | 99.56% | 0.44% |
| | *Value Weighted* | | | | | | |
| | Decile 1 | 80.96% | 42.21% | 47.09% | 64.92% | 0.00% | 100.00% |
| | Deciles 2-9 | 93.78% | 48.24% | 23.68% | 70.54% | 54.42% | 45.58% |
| | Decile 10 | 83.96% | 46.50% | 40.31% | 66.01% | 99.52% | 0.48% |
| | **Past 1-Year Returns** | | | | | | |
| | *Equal Weighted* | | | | | | |
| | Decile 1 | 29.26% | 41.82% | 76.37% | 40.28% | 0.01% | 33.62% |
| | Deciles 2-9 | 52.55% | 51.18% | 45.49% | 51.49% | 8.83% | 4.67% |
| | Decile 10 | 50.48% | 48.86% | 59.54% | 48.05% | 34.16% | 0.08% |
| | *Value Weighted* | | | | | | |
| | Decile 1 | 70.41% | 40.56% | 62.97% | 59.05% | 0.00% | 41.38% |
| | Deciles 2-9 | 93.68% | 48.36% | 23.64% | 70.84% | 18.89% | 3.39% |
| | Decile 10 | 89.41% | 44.99% | 36.14% | 67.30% | 59.24% | 0.01% |
| | **Past 3-Year Returns** | | | | | | |
| | *Equal Weighted* | | | | | | |
| | Decile 1 | 26.69% | 55.21% | 77.69% | 41.32% | 0.04% | 30.43% |
| | Deciles 2-9 | 51.67% | 50.96% | 46.44% | 50.39% | 11.18% | 3.53% |
| | Decile 10 | 59.94% | 37.42% | 50.78% | 55.67% | 44.31% | 0.11% |
| | *Value Weighted* | | | | | | |
| | Decile 1 | 69.22% | 57.38% | 62.79% | 58.68% | 0.15% | 36.85% |
| | Deciles 2-9 | 93.52% | 49.79% | 23.65% | 70.08% | 31.17% | 2.26% |
| | Decile 10 | 92.00% | 34.83% | 31.23% | 72.65% | 76.63% | 0.01% |

† Volume turnover is defined separately for NYSE-AMEX and NASDAQ stocks due to different conventions in recorded volume on the exchanges. The volume/turnover numbers are scaled by the means of these numbers for their exchange in order to account for this institutional discrepancy. Calculated from January, 1976 onward for NYSE-AMEX firms and January, 1983 onward for NASDAQ firms.

‡ Calculated from January, 1981 onward, when data became available.

## Table 2:
## Winner, Loser, and Consistency Effects of Past Returns Across Seasons

Fama and MacBeth (1973) cross-sectional regressions are run every month on all NYSE, AMEX, and NASDAQ-NMS securities from August, 1966 to July, 1995. The cross-section of *hedged* 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 hedged 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. The past return variables include the return on the stock from the previous month ($r_{-1:-1}$), previous year (cumulative return from month $t-12$ to month $t-2$, $r_{-12:-2}$), and previous three years (cumulative return from month $t-36$ to month $t-13$, $r_{-36:-13}$), with interactions between each past return and a dummy indicating if that past return was negative, $r^L_{-t2:-t1}(j) = min(0, r_{-t2:-t1}(j))$. Also included are consistent winner and loser dummies, $D^{CW}_{-t2:-t1}$ and $D^{CL}_{-t2:-t1}$, respectively. If the stock had a positive return last month, $D^{CW}_{-1:-1} = 1$; ($D^{CW}_{-12:-2} = 1$) (or ($D^{CL}_{-12:-2} = 1$)) if the stock exhibited positive (negative) returns in at least 8 of the 1-year horizon's 11 months; $D^{CW}_{-36:-13} = 1$ (or $D^{CL}_{-36:-13} = 1$) if the stock exhibited positive (negative) returns in at least 15 of the 3-year horizon's 24 months. The functional form of the month $t$ cross-sectional regression is,

$$\begin{aligned}
\tilde{r}_t(j) - \tilde{R}^B_t(j) &= \alpha_t + \beta_{1t} r_{t-1:t-1}(j) + \beta_{2t} r^L_{t-1:t-1}(j) + \beta_{3t} D^{CW}_{t-1:t-1}(j) \\
&+ \gamma_{1t} r_{t-12:t-2}(j) + \gamma_{2t} r^L_{t-12:t-2}(j) + \gamma_{3t} D^{CW}_{t-12:t-2}(j) + \gamma_{4t} D^{CL}_{t-12:t-2}(j) \\
&+ \delta_{1t} r_{t-36:t-13}(j) + \delta_{2t} r^L_{t-36:t-13}(j) + \delta_{3t} D^{CW}_{t-36:t-13}(j) + \delta_{4t} D^{CL}_{t-36:t-13}(j) \\
&+ \tilde{\epsilon}_t(j),
\end{aligned}$$

where $\tilde{r}_t(j)$ is stock $j$'s return in month $t$, $\tilde{R}^B_t(j)$ is stock $j$'s benchmark portfolio return in month $t$. The coefficients from these cross-sectional regressions are averaged over time in the style of Fama and MacBeth (1973) and time-series $t$-statistics are reported in parentheses over all months, for the month of January only, from February to November only, and for December only.

| **Dependent Variable:** | *Cross-Section of Size, BE/ME, and Industry Hedged Returns* | | | |
|---|---|---|---|---|
| **Regressors:** | All Months | January | February-November | December |
| $r_{-1:-1}$ | -0.0472 | -0.1002 | -0.0436 | -0.0431 |
| | (-11.39) | (-4.44) | (-10.34) | (-3.54) |
| $r^L_{-1:-1}$ | -0.0764 | -0.2189 | -0.0606 | -0.0921 |
| | (-9.63) | (-6.79) | (-7.19) | (-4.20) |
| $D^{CW}_{-1:-1}$ | 0.0051 | 0.0097 | 0.0048 | 0.0060 |
| | (8.79) | (2.73) | (8.62) | (3.10) |
| $r_{-12:-2}$ | 0.0028 | -0.0072 | 0.0029 | 0.0075 |
| | (2.50) | (-1.88) | (2.38) | (2.17) |
| $r^L_{-12:-2}$ | 0.0113 | -0.0725 | 0.0170 | 0.0440 |
| | (2.97) | (-3.57) | (4.62) | (4.72) |
| $D^{CW}_{-12:-2}$ | 0.0046 | 0.0126 | 0.0042 | 0.0017 |
| | (5.80) | (2.61) | (5.30) | (0.67) |
| $D^{CL}_{-12:-2}$ | -0.0007 | 0.0044 | -0.0014 | 0.0011 |
| | (-0.76) | (1.18) | (-1.29) | (0.40) |
| $r_{-36:-13}$ | -0.0015 | -0.0002 | -0.0021 | 0.0023 |
| | (-3.47) | (-0.10) | (-4.28) | (1.42) |
| $r^L_{-36:-13}$ | -0.0052 | -0.0537 | -0.0025 | 0.0159 |
| | (-2.04) | (-3.91) | (-1.02) | (2.31) |
| $D^{CW}_{-36:-13}$ | 0.0014 | 0.0040 | 0.0011 | 0.0010 |
| | (2.73) | (1.93) | (2.03) | (0.63) |
| $D^{CL}_{-36:-13}$ | -0.0007 | 0.0108 | -0.0015 | -0.0036 |
| | (-0.80) | (2.06) | (-1.78) | (-1.22) |

Table 3:
Is the Relation Between Past and Expected Returns Economically Significant?

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 2, stocks are ranked each month and grouped into rank-based decile portfolios, with decile 10 having the highest predicted return. Both equal- and value-weighted decile portfolio returns of the hedged (with respect to size, BE/ME, and industry) positions in stocks are computed. 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. Time-series average returns and annualized standard deviations are reported over all months for each decile, along with the difference between decile 10 (highest predicted return) and decile 1 (lowest predicted return) and the corresponding $t$-statistic for this difference. Panel A uses all regression coefficients to score and rank stocks. Panel B excludes the three regression coefficients corresponding to the 1-month past return regressors to rank stocks. Panel C uses only the four regression coefficients corresponding to 1-year past return regressors to rank stocks, and Panel D uses only the four regression coefficients corresponding to 3-year past return regressors to rank stocks.

| | Deciles | | | | | | | | | | 10 − 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | (t-stat) |
| **Panel A: All Regressors** | | | | | | | | | | | |
| VW | -0.0047 | -0.0035 | -0.0023 | -0.0012 | 0.0012 | 0.0012 | 0.0029 | 0.0051 | 0.0062 | 0.0092 | 0.0139 |
| stdev. | 0.0693 | 0.0456 | 0.0465 | 0.0520 | 0.0486 | 0.0464 | 0.0490 | 0.0532 | 0.0693 | 0.1104 | (6.48) |
| EW | -0.0065 | -0.0046 | -0.0026 | -0.0007 | 0.0009 | 0.0016 | 0.0027 | 0.0041 | 0.0076 | 0.0215 | 0.0280 |
| stdev. | 0.0518 | 0.0428 | 0.0430 | 0.0404 | 0.0375 | 0.0328 | 0.0336 | 0.0325 | 0.0462 | 0.1052 | (12.85) |
| **Panel B: Exclude Past 1-Month Regressors** | | | | | | | | | | | |
| VW | -0.0051 | -0.0035 | -0.0018 | -0.0002 | -0.0004 | 0.0015 | 0.0025 | 0.0026 | 0.0040 | 0.0061 | 0.0111 |
| stdev. | 0.0796 | 0.0606 | 0.0598 | 0.0516 | 0.0549 | 0.0500 | 0.0630 | 0.0576 | 0.0520 | 0.1016 | (4.94) |
| EW | -0.0055 | -0.0039 | -0.0023 | -0.0002 | 0.0011 | 0.0019 | 0.0027 | 0.0043 | 0.0056 | 0.0113 | 0.0168 |
| stdev. | 0.0587 | 0.0444 | 0.0444 | 0.0385 | 0.0347 | 0.0354 | 0.0344 | 0.0414 | 0.0437 | 0.0984 | (7.77) |
| **Panel C: Past 1-Year Regressors Only** | | | | | | | | | | | |
| VW | -0.0021 | -0.0018 | -0.0014 | -0.0011 | -0.0007 | 0.0002 | 0.0026 | 0.0040 | 0.0034 | 0.0049 | 0.0071 |
| stdev. | 0.0680 | 0.0553 | 0.0602 | 0.0460 | 0.0519 | 0.0518 | 0.0658 | 0.0512 | 0.0589 | 0.0865 | (3.63) |
| EW | -0.0050 | -0.0038 | -0.0026 | -0.0012 | -0.0001 | 0.0017 | 0.0036 | 0.0048 | 0.0058 | 0.0110 | 0.0160 |
| stdev. | 0.0480 | 0.0410 | 0.0438 | 0.0412 | 0.0383 | 0.0383 | 0.0434 | 0.0442 | 0.0452 | 0.0843 | (8.66) |
| **Panel D: Past 3-Year Regressors Only** | | | | | | | | | | | |
| VW | 0.0008 | 0.0005 | 0.0001 | -0.0008 | 0.0009 | -0.0012 | 0.0017 | 0.0016 | 0.0033 | 0.0026 | 0.0017 |
| stdev. | 0.0474 | 0.0402 | 0.0513 | 0.0577 | 0.0681 | 0.0605 | 0.0662 | 0.0616 | 0.0855 | 0.0931 | (1.02) |
| EW | 0.0004 | 0.0003 | 0.0002 | -0.0007 | -0.0014 | -0.0017 | 0.0026 | 0.0027 | 0.0036 | 0.0063 | 0.0059 |
| stdev. | 0.0382 | 0.0381 | 0.0472 | 0.0540 | 0.0600 | 0.0597 | 0.0693 | 0.0586 | 0.0600 | 0.0866 | (3.52) |

Table 4:
In- and Out-of-Sample Profits Across Segments of the Market

Profits from the stock ranking system of Table 3 are reported below both in and out of sample. Stocks are ranked each month by their predicted return and grouped into rank-based deciles, with decile 10 having the highest predicted return. The value-weighted hedged (with respect to size, BE/ME, and industry) return of each decile portfolio is computed. 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 (in parentheses) of the spread between the best and worst-ranked decile portfolios are reported. The regression coefficients are estimated over the entire August, 1966 to July, 1995 time period and used to rank stocks. The first four columns of each panel report profits in sample over the period January, 1966 to July, 1995 and the second four columns of each panel report the profits of these same strategies out of sample over the period August, 1995 to December, 1999. Profits are reported for stock ranking systems that employ all coefficients, exclude those associated with 1-month returns, employ only the 1-year past return coefficients, and employ only the 3-year past return coefficients, respectively. Panel A reports monthly profits for all CRSP-listed equities. Panel B reports profits for stocks with share prices that exceed $5. Panel C reports profits for the smallest and largest quintile of stocks (using NYSE market capitalization breakpoints). Panel D reports the profits for the lowest and highest quintile of stocks based on book-to-market equity firms within the smallest and largest third of stocks. 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 (beginning January, 1976) and NASDAQ-NMS traded stocks separately (beginning January, 1983). Panel F reports the profits for the lowest and highest quintile of stocks based on fraction of institutional ownership (beginning January, 1981) within the smallest and largest third of stocks. Profits are reported for all months, January only, February to November only, and December only.

| Return Period: | **In Sample Aug., 1966 - July, 1995** | | | | **Out of Sample Aug., 1995 - Dec., 1999** | | | |
|---|---|---|---|---|---|---|---|---|
| | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns |
| | **Panel A: All Stocks** | | | | | | | |
| All | 0.0139 | 0.0111 | 0.0071 | 0.0017 | 0.0203 | 0.0075 | 0.0065 | 0.0361 |
| | (0.136) | (0.141) | (0.123) | (0.108) | (0.147) | (0.181) | (0.132) | (0.179) |
| Jan. | 0.0454 | 0.0435 | 0.0155 | 0.0405 | 0.0112 | 0.0057 | 0.0081 | 0.0099 |
| | (0.252) | (0.256) | (0.193) | (0.147) | (0.180) | (0.052) | (0.072) | (0.112) |
| Feb.-Nov. | 0.0088 | 0.0067 | 0.0060 | -0.0029 | 0.0236 | 0.0063 | 0.0051 | 0.0416 |
| | (0.112) | (0.119) | (0.111) | (0.096) | (0.163) | (0.215) | (0.151) | (0.207) |
| Dec. | 0.0301 | 0.0174 | 0.0080 | 0.0056 | 0.0043 | 0.0259 | 0.0206 | 0.0317 |
| | (0.131) | (0.147) | (0.156) | (0.098) | (0.110) | (0.098) | (0.102) | (0.086) |
| | **Panel B: Excluding Stocks with Share Prices Below $5** | | | | | | | |
| All | 0.0135 | 0.0100 | 0.0077 | 0.0016 | 0.0179 | 0.0129 | 0.0121 | 0.0038 |
| | (0.130) | (0.136) | (0.128) | (0.087) | (0.162) | (0.170) | (0.168) | (0.099) |
| Jan. | 0.0433 | 0.0347 | 0.0138 | 0.0243 | 0.0029 | 0.0098 | 0.0138 | -0.0082 |
| | (0.198) | (0.183) | (0.183) | (0.118) | (0.135) | (0.102) | (0.127) | (0.034) |
| Feb.-Nov. | 0.0090 | 0.0069 | 0.0071 | -0.0024 | 0.0221 | 0.0140 | 0.0152 | 0.0065 |
| | (0.113) | (0.127) | (0.116) | (0.068) | (0.184) | (0.198) | (0.192) | (0.116) |
| Dec. | 0.0234 | 0.0137 | 0.0067 | 0.0031 | 0.0217 | 0.0315 | 0.0172 | 0.0111 |
| | (0.145) | (0.144) | (0.166) | (0.070) | (0.082) | (0.121) | (0.159) | (0.044) |

| Return Period: | In Sample Aug., 1966 - July, 1995 | | | | Out of Sample Aug., 1995 - Dec., 1999 | | | |
|---|---|---|---|---|---|---|---|---|
| | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns |
| | **Panel C: Across Size (Market Capitalization) Quintiles** | | | | | | | |
| | *Smallest Size Quintile (NYSE Breakpoints)* | | | | | | | |
| All | 0.0314 | 0.0201 | 0.0170 | 0.0037 | 0.0220 | 0.0070 | -0.0010 | 0.0364 |
| | (0.178) | (0.165) | (0.134) | (0.127) | (0.145) | (0.111) | (0.101) | (0.201) |
| Jan. | 0.1113 | 0.0828 | 0.0547 | 0.0547 | -0.0103 | -0.0127 | -0.0077 | 0.0252 |
| | (0.410) | (0.397) | (0.285) | (0.237) | (0.116) | (0.043) | (0.096) | (0.148) |
| Feb.-Nov. | 0.0241 | 0.0123 | 0.0123 | -0.0022 | 0.0310 | 0.0100 | -0.0002 | 0.0428 |
| | (0.109) | (0.100) | (0.102) | (0.100) | (0.158) | (0.128) | (0.109) | (0.222) |
| Dec. | 0.0313 | 0.0373 | 0.0301 | 0.0112 | 0.0016 | 0.0156 | 0.0106 | 0.0092 |
| | (0.114) | (0.131) | (0.109) | (0.078) | (0.075) | (0.058) | (0.083) | (0.105) |
| | *Largest Size Quintile (NYSE Breakpoints)* | | | | | | | |
| All | 0.0089 | 0.0052 | 0.0056 | 0.0014 | 0.0116 | 0.0170 | 0.0151 | 0.0066 |
| | (0.104) | (0.113) | (0.109) | (0.093) | (0.130) | (0.203) | (0.197) | (0.120) |
| Jan. | 0.0272 | 0.0291 | 0.0167 | 0.0213 | 0.0207 | -0.0010 | 0.0073 | -0.0096 |
| | (0.171) | (0.151) | (0.173) | (0.086) | (0.135) | (0.086) | (0.128) | (0.072) |
| Feb.-Nov. | 0.0069 | 0.0031 | 0.0044 | -0.0008 | 0.0126 | 0.0221 | 0.0168 | 0.0103 |
| | (0.096) | (0.107) | (0.102) | (0.093) | (0.147) | (0.243) | (0.233) | (0.137) |
| Dec. | 0.0130 | 0.0028 | 0.0070 | 0.0035 | -0.0015 | 0.0211 | 0.0225 | 0.0171 |
| | (0.081) | (0.109) | (0.111) | (0.089) | (0.077) | (0.047) | (0.108) | (0.053) |

| Return Period: | In Sample Aug., 1966 - July, 1995 | | | | Out of Sample Aug., 1995 - Dec., 1999 | | | |
|---|---|---|---|---|---|---|---|---|
| | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns |
| **Panel D: Across Book-to-Market Equity Quintiles** | | | | | | | | |
| *Lowest BE/ME Quintile (Smallest 1/3 Market Cap.)* | | | | | | | | |
| All | 0.0271 | 0.0205 | 0.0192 | 0.0045 | 0.0237 | -0.0052 | -0.0087 | 0.0311 |
| | (0.180) | (0.177) | (0.146) | (0.140) | (0.177) | (0.144) | (0.162) | (0.185) |
| Jan. | 0.1017 | 0.0717 | 0.0459 | 0.0546 | -0.0132 | -0.0302 | -0.0211 | 0.0304 |
| | (0.370) | (0.382) | (0.271) | (0.221) | (0.155) | (0.146) | (0.145) | (0.221) |
| Feb.-Nov. | 0.0204 | 0.0140 | 0.0160 | -0.0007 | 0.0352 | -0.0077 | -0.0098 | 0.0313 |
| | (0.127) | (0.130) | (0.125) | (0.121) | (0.187) | (0.146) | (0.176) | (0.191) |
| Dec. | 0.0245 | 0.0387 | 0.0291 | 0.0049 | -0.0062 | 0.0176 | 0.0162 | 0.0012 |
| | (0.146) | (0.155) | (0.149) | (0.107) | (0.103) | (0.051) | (0.161) | (0.165) |
| *Highest BE/ME Quintile (Smallest 1/3 Market Cap.)* | | | | | | | | |
| All | 0.0236 | 0.0174 | 0.0122 | 0.0023 | 0.0135 | 0.0087 | 0.0031 | 0.0109 |
| | (0.189) | (0.181) | (0.144) | (0.151) | (0.144) | (0.082) | (0.097) | (0.097) |
| Jan. | 0.0943 | 0.0746 | 0.0466 | 0.0582 | -0.0036 | 0.0156 | 0.0105 | 0.0098 |
| | (0.418) | (0.436) | (0.320) | (0.251) | (0.108) | (0.071) | (0.095) | (0.078) |
| Feb.-Nov. | 0.0163 | 0.0106 | 0.0079 | -0.0045 | 0.0183 | 0.0074 | 0.0004 | 0.0101 |
| | (0.133) | (0.119) | (0.107) | (0.128) | (0.162) | (0.082) | (0.093) | (0.084) |
| Dec. | 0.0301 | 0.0308 | 0.0228 | 0.0114 | -0.0080 | 0.0207 | 0.0168 | 0.0152 |
| | (0.119) | (0.146) | (0.139) | (0.106) | (0.120) | (0.085) | (0.126) | (0.091) |
| *Lowest BE/ME Quintile (Largest 1/3 Market Cap.)* | | | | | | | | |
| All | 0.0082 | 0.0077 | 0.0084 | 0.0006 | 0.0176 | 0.0082 | 0.0150 | -0.0061 |
| | (0.128) | (0.143) | (0.132) | (0.119) | (0.163) | (0.143) | (0.162) | (0.120) |
| Jan. | 0.0201 | 0.0262 | 0.0143 | 0.0261 | 0.0084 | -0.0072 | 0.0213 | -0.0391 |
| | (0.217) | (0.192) | (0.203) | (0.117) | (0.187) | (0.150) | (0.166) | (0.111) |
| Feb.-Nov. | 0.0063 | 0.0056 | 0.0078 | -0.0020 | 0.0183 | 0.0070 | 0.0069 | -0.0003 |
| | (0.118) | (0.137) | (0.125) | (0.118) | (0.169) | (0.156) | (0.160) | (0.118) |
| Dec. | 0.0162 | 0.0112 | 0.0115 | -0.0003 | 0.0138 | 0.0188 | 0.0011 | 0.0027 |
| | (0.116) | (0.149) | (0.126) | (0.109) | (0.236) | (0.100) | (0.061) | (0.058) |
| *Highest BE/ME Quintile (Largest 1/3 Market Cap.)* | | | | | | | | |
| All | 0.0087 | 0.0060 | 0.0033 | 0.0009 | 0.0051 | 0.0023 | -0.0013 | 0.0035 |
| | (0.146) | (0.148) | (0.146) | (0.125) | (0.135) | (0.125) | (0.123) | (0.107) |
| Jan. | 0.0295 | 0.0326 | 0.0185 | 0.0285 | -0.0015 | 0.0147 | 0.0033 | 0.0176 |
| | (0.238) | (0.204) | (0.228) | (0.153) | (0.066) | (0.187) | (0.089) | (0.108) |
| Feb.-Nov. | 0.0075 | 0.0035 | 0.0011 | -0.0008 | 0.0027 | -0.0020 | -0.0064 | 0.0038 |
| | (0.134) | (0.142) | (0.138) | (0.121) | (0.148) | (0.123) | (0.136) | (0.111) |
| Dec. | 0.0021 | 0.0057 | 0.0095 | -0.0108 | 0.0055 | 0.0166 | 0.0119 | -0.0060 |
| | (0.141) | (0.142) | (0.128) | (0.110) | (0.151) | (0.163) | (0.064) | (0.093) |

| Return Period: | In Sample Jan., 1976 - July, 1995 | | | | Out of Sample Aug., 1995 - Dec., 1999 | | | |
|---|---|---|---|---|---|---|---|---|
| | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns |
| | **Panel E: Across Trading Volume (Turnover) Quintiles** | | | | | | | |
| | *Lowest Volume Quintile (NYSE-AMEX Only)* | | | | | | | |
| All | 0.0116 | 0.0043 | 0.0043 | 0.0001 | 0.0166 | 0.0121 | 0.0062 | 0.0057 |
| | (0.106) | (0.099) | (0.104) | (0.090) | (0.176) | (0.112) | (0.100) | (0.200) |
| Jan. | 0.0241 | 0.0193 | 0.0103 | 0.0174 | 0.0273 | 0.0250 | 0.0109 | -0.0062 |
| | (0.178) | (0.112) | (0.130) | (0.088) | (0.052) | (0.093) | (0.086) | (0.025) |
| Feb.-Nov. | 0.0104 | 0.0030 | 0.0043 | -0.0022 | 0.0157 | 0.0094 | 0.0028 | -0.0013 |
| | (0.099) | (0.099) | (0.102) | (0.088) | (0.206) | (0.120) | (0.106) | (0.151) |
| Dec. | 0.0146 | 0.0026 | -0.0003 | 0.0047 | 0.0043 | -0.0108 | 0.0131 | 0.0720 |
| | (0.070) | (0.092) | (0.111) | (0.107) | (0.081) | (0.058) | (0.073) | (0.585) |
| | *Highest Volume Quintile (NYSE-AMEX Only)* | | | | | | | |
| All | 0.0154 | 0.0146 | 0.0100 | 0.0007 | 0.0147 | 0.0068 | 0.0064 | 0.0228 |
| | (0.181) | (0.175) | (0.157) | (0.151) | (0.190) | (0.178) | (0.154) | (0.151) |
| Jan. | 0.0564 | 0.0442 | 0.0168 | 0.0407 | -0.0167 | 0.0172 | 0.0371 | -0.0088 |
| | (0.342) | (0.320) | (0.205) | (0.171) | (0.210) | (0.109) | (0.168) | (0.084) |
| Feb.-Nov. | 0.0113 | 0.0127 | 0.0092 | -0.0031 | 0.0218 | 0.0075 | 0.0033 | 0.0244 |
| | (0.148) | (0.153) | (0.152) | (0.138) | (0.208) | (0.195) | (0.162) | (0.176) |
| Dec. | 0.0186 | 0.0067 | 0.0142 | -0.0032 | 0.0134 | 0.0178 | 0.0186 | 0.0388 |
| | (0.209) | (0.165) | (0.170) | (0.206) | (0.098) | (0.091) | (0.121) | (0.030) |
| | *Lowest Volume Quintile (NASDAQ Only–Jan., 1983-)* | | | | | | | |
| All | 0.0176 | 0.0114 | 0.0104 | 0.0016 | 0.0408 | 0.0241 | 0.0206 | 0.0002 |
| | (0.158) | (0.142) | (0.154) | (0.119) | (0.294) | (0.330) | (0.261) | (0.141) |
| Jan. | 0.0436 | 0.0175 | 0.0007 | 0.0174 | 0.0774 | 0.0403 | 0.0391 | -0.0261 |
| | (0.286) | (0.270) | (0.224) | (0.197) | (0.282) | (0.136) | (0.152) | (0.082) |
| Feb.-Nov. | 0.0141 | 0.0097 | 0.0101 | -0.0021 | 0.0396 | 0.0373 | 0.0234 | 0.0069 |
| | (0.132) | (0.120) | (0.141) | (0.106) | (0.316) | (0.365) | (0.311) | (0.153) |
| Dec. | 0.0206 | 0.0182 | 0.0116 | 0.0169 | -0.0103 | -0.0514 | -0.0067 | -0.0186 |
| | (0.191) | (0.143) | (0.178) | (0.116) | (0.102) | (0.374) | (0.081) | (0.069) |
| | *Highest Volume Quintile (NASDAQ Only–Jan.,1983-)* | | | | | | | |
| All | 0.0330 | 0.0196 | 0.0125 | 0.0069 | 0.0098 | 0.0152 | 0.0065 | 0.0677 |
| | (0.248) | (0.261) | (0.216) | (0.175) | (0.254) | (0.359) | (0.271) | (0.308) |
| Jan. | 0.1277 | 0.1177 | 0.0425 | 0.0352 | -0.0323 | -0.0021 | -0.0188 | 0.0041 |
| | (0.399) | (0.541) | (0.330) | (0.247) | (0.208) | (0.263) | (0.167) | (0.306) |
| Feb.-Nov. | 0.0236 | 0.0075 | 0.0063 | 0.0033 | 0.0197 | 0.0069 | 0.0001 | 0.0757 |
| | (0.210) | (0.184) | (0.192) | (0.167) | (0.272) | (0.406) | (0.298) | (0.324) |
| Dec. | 0.0282 | 0.0353 | 0.0313 | 0.0102 | -0.0336 | 0.0501 | 0.0351 | 0.0416 |
| | (0.186) | (0.252) | (0.258) | (0.160) | (0.219) | (0.386) | (0.363) | (0.216) |

| Return Period: | In Sample Jan., 1981 - July, 1995 | | | | Out of Sample Aug., 1995 - Dec., 1999 | | | |
|---|---|---|---|---|---|---|---|---|
| | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns | All | Ex. 1-Month Returns | Past 1-Year Returns | Past 3-Year Returns |
| | **Panel F: Across Institutional Ownership Quintiles** | | | | | | | |
| | *Lowest Institutional Ownership Quintile (Smallest 1/3 Market Cap.)* | | | | | | | |
| All | 0.0224 | 0.0219 | 0.0214 | -0.0002 | 0.0280 | 0.0069 | -0.0030 | 0.0482 |
| | (0.163) | (0.165) | (0.131) | (0.135) | (0.161) | (0.161) | (0.117) | (0.232) |
| Jan. | 0.1021 | 0.0983 | 0.0714 | 0.0534 | 0.0026 | -0.0127 | -0.0058 | 0.0482 |
| | (0.299) | (0.357) | (0.270) | (0.196) | (0.124) | (0.117) | (0.094) | (0.207) |
| Feb.-Nov. | 0.0132 | 0.0134 | 0.0149 | -0.0071 | 0.0335 | 0.0054 | -0.0038 | 0.0538 |
| | (0.105) | (0.100) | (0.083) | (0.117) | (0.177) | (0.183) | (0.133) | (0.247) |
| Dec. | 0.0267 | 0.0364 | 0.0239 | 0.0180 | 0.0002 | 0.0187 | 0.0048 | 0.0130 |
| | (0.132) | (0.123) | (0.117) | (0.071) | (0.045) | (0.118) | (0.065) | (0.118) |
| | *Highest Institutional Ownership Quintile (Smallest 1/3 Market Cap.)* | | | | | | | |
| All | 0.0151 | 0.0110 | 0.0118 | -0.0012 | 0.0169 | 0.0014 | -0.0121 | 0.0387 |
| | (0.175) | (0.155) | (0.155) | (0.168) | (0.178) | (0.183) | (0.161) | (0.211) |
| Jan. | 0.0371 | 0.0143 | 0.0065 | 0.0278 | -0.0153 | -0.0113 | -0.0422 | 0.0251 |
| | (0.185) | (0.217) | (0.154) | (0.145) | (0.154) | (0.148) | (0.135) | (0.136) |
| Feb.-Nov. | 0.0118 | 0.0112 | 0.0122 | -0.0047 | 0.0208 | -0.0009 | -0.0119 | 0.0490 |
| | (0.172) | (0.150) | (0.152) | (0.164) | (0.193) | (0.194) | (0.159) | (0.228) |
| Dec. | 0.0189 | 0.0119 | 0.0002 | 0.0097 | 0.0182 | 0.0569 | 0.0298 | 0.0260 |
| | (0.169) | (0.153) | (0.161) | (0.235) | (0.182) | (0.139) | (0.169) | (0.053) |
| | *Lowest Institutional Ownership Quintile (Largest 1/3 Market Cap.)* | | | | | | | |
| All | 0.0048 | 0.0058 | 0.0018 | 0.0013 | 0.0124 | 0.0185 | 0.0147 | 0.0105 |
| | (0.164) | (0.153) | (0.153) | (0.135) | (0.170) | (0.223) | (0.209) | (0.134) |
| Jan. | 0.0244 | 0.0318 | 0.0208 | 0.0230 | 0.0003 | 0.0091 | 0.0073 | -0.0331 |
| | (0.220) | (0.179) | (0.165) | (0.162) | (0.091) | (0.109) | (0.227) | (0.091) |
| Feb.-Nov. | 0.0011 | 0.0018 | -0.0019 | 0.0000 | 0.0114 | 0.0201 | 0.0135 | 0.0180 |
| | (0.150) | (0.145) | (0.146) | (0.132) | (0.188) | (0.260) | (0.235) | (0.140) |
| Dec. | 0.0091 | 0.0211 | -0.0012 | 0.0000 | 0.0418 | 0.0481 | 0.0304 | 0.0043 |
| | (0.192) | (0.178) | (0.148) | (0.142) | (0.228) | (0.172) | (0.160) | (0.050) |
| | *Highest Institutional Ownership Quintile (Largest 1/3 Market Cap.)* | | | | | | | |
| All | 0.0085 | 0.0055 | 0.0083 | 0.0020 | 0.0113 | 0.0152 | 0.0118 | 0.0092 |
| | (0.120) | (0.113) | (0.114) | (0.093) | (0.136) | (0.212) | (0.202) | (0.118) |
| Jan. | 0.0232 | 0.0263 | 0.0217 | 0.0235 | 0.0182 | -0.0128 | 0.0192 | -0.0139 |
| | (0.174) | (0.183) | (0.145) | (0.107) | (0.162) | (0.116) | (0.176) | (0.076) |
| Feb.-Nov. | 0.0063 | 0.0046 | 0.0062 | 0.0009 | 0.0150 | 0.0223 | 0.0137 | 0.0113 |
| | (0.106) | (0.103) | (0.097) | (0.089) | (0.146) | (0.251) | (0.232) | (0.130) |
| Dec. | 0.0050 | -0.0044 | -0.0018 | -0.0012 | -0.0178 | 0.0026 | 0.0273 | 0.0178 |
| | (0.105) | (0.087) | (0.131) | (0.082) | (0.083) | (0.051) | (0.044) | (0.022) |

Table 5:
How Does Tax-Loss Trading Affect the Relation Between Past and Expected Returns?

Profits are reported from the stock ranking system of Table 3 during different tax regimes based on the maximum short-term capital gains tax rate. Stocks are ranked each month by their predicted return and grouped into rank-based deciles, with decile 10 having the highest predicted return. The value-weighted hedged (with respect to size, BE/ME, and industry) return of each decile portfolio is computed. The time-series average of the August, 1966 to July, 1995 regression coefficients (excluding 1-month regressors) 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. Panel A conducts formal tests of tax regime effects by reporting time-series regression coefficients of the profits on seasonal dummies, tax regime dummies, and their interactions. $t$-statistics on the coefficients are reported in parentheses. Since tax-loss selling should predominantly apply to past losing stocks and since the trading strategy shorts losers in December (due to continuation) and buys losers in January (due to reversals), profits are reported separately for decile 1 in December and decile 10 in January in Panels B and C, respectively. Average monthly returns and annualized standard deviations (in parentheses) of the worst and best-ranked decile portfolios are reported for December and January, respectively, across the two tax regimes. These profits are reported for the smallest and largest quintile of stocks (using NYSE breakpoints), and lowest and highest institutional ownership (%IO) quintile of stocks among the smallest and largest third of stocks over the period August, 1966 to December, 1999. The "high tax years" are 1968-69, 1981, 1972-75, 1985-86, and 1988-99. Panel B reports profits over the "low tax years", which are the remaining years.

| Profits: | **Aug., 1966 - Dec., 1999** | | | | | |
|---|---|---|---|---|---|---|
| Strategy: | Exclude 1-Month Regressors | | | | | |
| | **Panel A: Time-Series Regression** | | | | | |
| | constant | High Tax | High Tax Jan. | High Tax Dec. | Jan. | Dec. |
| All Stocks | 0.0033 | 0.0042 | 0.0364** | 0.0451** | 0.0129 | -0.0068 |
| | (0.88) | (0.88) | (2.39) | (3.30) | (1.00) | (-0.55) |
| | | | Smallest 1/3 Size | | Largest 1/3 Size | |
| | Smallest Size Quintile | Largest Size Quintile | Lowest %IO Quintile | Highest %IO Quintile | Lowest %IO Quintile | Highest %IO Quintile |
| | **Panel B: Decile 1 in December Across Tax Regimes** | | | | | |
| High Tax Dec. | -0.0278 | -0.0139 | -0.0339 | -0.0303 | -0.0132 | -0.0101 |
| | (0.134) | (0.089) | (0.170) | (0.221) | (0.139) | (0.092) |
| Low Tax Dec. | -0.0111 | 0.0050 | -0.0157 | -0.0063 | 0.0057 | 0.0060 |
| | (0.103) | (0.067) | (0.146) | (0.089) | (0.069) | (0.071) |
| | **Panel C: Decile 10 in January Across Tax Regimes** | | | | | |
| High Tax Jan. | 0.0553 | 0.0378 | 0.0541 | 0.0156 | 0.0342 | 0.0369 |
| | (0.328) | (0.152) | (0.252) | (0.233) | (0.171) | (0.158) |
| Low Tax Jan. | 0.0357 | 0.0282 | 0.0404 | 0.0323 | 0.0192 | 0.0247 |
| | (0.139) | (0.124) | (0.141) | (0.126) | (0.145) | (0.138) |

*,**Indicates significant at the 5% and 1% levels, respectively.