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Predicting stock price movements from past returns: the role of consistency and tax-loss selling ☆

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Abstract

The consistency of positive past returns and tax-loss selling significantly affects the relation between past returns and the cross-section of expected returns. Analysis of these additional effects across stock characteristics, seasons, and tax regimes provides clues about the sources of temporal relations in stock returns, pointing to potential explanations for this relation. A parsimonious trading rule generates surprisingly large economic returns despite controls for confounding sources of return premia, microstructure effects, and data snooping biases.

JEL classification: G11; G12; G14

Keywords: Market efficiency; Return autocorrelation; Momentum; Tax-loss trading

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1. Introduction

Within the last two decades, researchers have discovered that past returns contain information about expected returns. Both short- (less than one month) and long-term (three-to-five year) past returns are inversely related to future average returns, while intermediate horizon past returns (three to 12 months) are positively related to future average returns. Classic papers include Jegadeesh (1990), DeBondt and Thaler (1985), and Jegadeesh and Titman (1993).[1]

A variety of explanations are offered for these relations. They range from data issues, such as microstructure and data snooping biases (Boudoukh et al., 1994; Conrad and Kaul, 1989; Lo and MacKinlay, 1988), to rational risk-based explanations (Conrad and Kaul, 1998; Berk et al., 1999; Chordia and Shivakumar, 2002; Bansal et al., 2002), to irrational behavioral stories (DeBondt and Thaler, 1985, 1987; Jegadeesh and Titman, 1993; Daniel et al., 1998; Barberis et al., 1998; Hong and Stein, 1999; Hong et al., 2000; Lee and Swaminathan, 2000; Grinblatt and Han, 2002). Despite the ability of creative theorists and talented critics of empirical work to explain the sign of an observed temporal return relation, the field of finance finds it difficult to reconcile theory with the exceptional profits generated by trading strategies that exploit these patterns. Moreover, only recently have theories evolved, and these generally of the behavioral variety, that explain these multi-horizon and opposite-signed temporal relations synthetically. Yet little empirical work analyzes these patterns simultaneously and, as we will show, there are additional complexities to these relations that appear inconsistent with most existing explanations.

Before proposing novel theories for these effects, we need to better understand whether past returns predict future returns because they are a proxy for a more fundamental variable that predicts returns. In this regard, we analyze the consistency and sign of the past return (over multiple past return horizons), as well as the degree to which tax-motivated trading generates these effects.

A key finding that comes out of this analysis 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 is a finding that is predicted by theories advanced in other papers. For instance, Grinblatt and Han (2002) argue that the disposition effect can generate such results. Watkins (2002) argues that information diffusion explains a consistency in stock returns. Consistency can also proxy for the inverse of volatility and this may affect average returns as a proxy for risk.

In addition, we highlight the importance of seasonalities associated with past returns and the degree to which tax-loss trading plays a role in past return predictability. If tax-loss trading tends to mask or reverse the fundamental effects

[1] DeBondt and Thaler (1987), Lo and MacKinlay (1988), Conrad and Kaul (1989), Lehman (1990), Boudoukh et al. (1994), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Hong et al. (2000), Grundy and Martin (2001), and Lee and Swaminathan (2000) all show autocorrelation in stock returns at various horizons.

that drive temporal return relations at certain times of the year, it would not be possible to uncover them without isolating these effects by season. For example, we find that for our sample period, the profitability of the three-year reversal strategy is largely confined to January. This suggests that a link between long-term reversals and intermediate-term momentum is tenuous because the latter effect does not exhibit this seasonality. We also find that returns are strongly negative in December for losing firms, pointing to tax-loss trading as the driver of a good portion of the profitability of momentum strategies as well as strategies that take advantage of the turn-of-the-year effect.

A host of papers analyze the January effect, including Dyl (1977), Roll (1983), Keim (1983, 1989), Reinganum (1983), Berges et al. (1984), Chan (1986), Lakonishok and Smidt (1988), Reinganum and Shapiro (1987), Dyl and Maberly (1992), and Poterba and Weisbenner (2001). Many of these papers allude to tax-loss trading as a possible source of the effect. 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. Grinblatt and Keloharju (2001, 2003) use this explanation for Finnish investors, for instance. By inferring buying and selling pressure from quoted daily spreads, Hvidkjaer (2001) shows year-end selling pressure in firms that have done poorly over the prior year and subsequent year-end buying pressure in these firms after the turn of the year. His patterns of trading mirror our seasonal return patterns.

We argue that tax avoidance behavior, as opposed to other explanations (e.g., window dressing), drives much of the relation between past returns and expected returns in December and January. This is 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. In such a case, contrarian strategies become relatively more profitable and the profits from momentum strategies decline. We show that value-weighted strategies developed from the past one-year and three-year patterns exhibit diminished profitability outside of January and December in low tax years. Existing explanations for temporal return relations, both behavioral and rational, do not predict that these effects would diminish in low tax years, or vary in strength by the season of a given year, suggesting that they cannot solely explain why past return predictability exists.

We also analyze which types of stocks lend themselves to the most profitable technical trading strategies. The profitability of our trading strategies varies greatly depending on firm size, institutional ownership, and turnover despite controls for size, book-to-market, and industry as sources of return premia. The seasonal variation also differs across these sectors of the stock market. The sector-based analysis helps in assessing extant theories advanced to explain why these temporal relations exist. For instance, small, high turnover stocks with low institutional ownership exhibit more pronounced past return and seasonal effects. This further points to tax-loss selling, as opposed to window dressing, being associated with these patterns.

Finally, our approach in analyzing the importance of these complex patterns of returns is based on a parsimonious stock ranking system derived from simple Fama-MacBeth cross-sectional regressions. We analyze the simultaneous effect of a number of past return-related variables on the future returns of hedged positions in individual stocks, which have their size, book-to-market, 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-related variable on the cross-section of expected returns by eliminating confounding sources of return premia and reducing volatility to generate more powerful tests. Moreover, the hedged stock approach generates zero-cost portfolios which, lacking risk under the null, have expected values of zero. This helps quantify asymmetric effects from past positive (winners) and negative (losers) returns, as well as consistent winners and losers. It also helps in analyzing the causes of seasonal effects. This approach can better offer clues about the source and profitability of trading strategies based on past returns.

The rest of the paper is organized as follows. Section 2 briefly describes the data and our empirical approach. Section 3 reports the coefficients and test statistics for Fama-MacBeth regressions that characterize how the past pattern of returns affects the cross-section of expected returns, including the consistency, season, and sign of the return. 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. The degree to which consistency, seasonalities, market micro-structure effects, and various past return horizons affect profitability is also examined. Section 5 studies whether the seasonal profitability of trading strategies across sectors of the stock market is indicative of tax-loss trading influencing the predictability of returns and how changing tax regimes affect this relation. Section 6 focuses on transaction costs and data snooping biases. Finally, Section 7 concludes the paper.

2. Data description and empirical approach

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 grouping two-digit Standard Industrial Classifications (SIC) of stocks into twenty value-weighted industry portfolios as in Moskowitz and Grinblatt

(1999). Data on book-to-market equity (BE/ME) make use of Compustat, where book value of equity is the most recent value from the prior fiscal year as defined in Fama and French (1992). 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 1983 on for NASDAQ, come 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 12 months. Tax rates, used to identify tax regime subsamples, are obtained from Pechman (1987) and Willan (1994) prior to 1995 and from the Internal Revenue Service from 1995 on. Unless otherwise specified, our tests pertain to all CRSP-listed 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).

2.1. Analyzing the cross-section of expected returns

We use cross-sectional regressions to assess the predictive power of the pattern of past returns. The dependent variable, which we refer to as a hedged return, adjusts returns for known sources of return premia. It is the difference between the return of a stock and the return of its benchmark portfolio. We shortly describe how we compute these hedged returns.

The regressions investigate the impact of past returns per se on a stock's hedged return, and whether the impact of the past returns is path and seasonally dependent. The past pattern of returns can provide clues about a deeper underlying cause of the predictive power of past returns. In particular, recent theories suggest the consistency of past returns should matter for expected returns. For instance, Watkins (2002) proposes a Bayesian learning model in which consistency interacts with the discount rate, and consistent positive (negative) returns are signals of lower (higher) discount rates. The change in the discount rate generates a detectable price reaction which is interpreted as momentum. Grinblatt and Han (2002) suggest that the disposition effect generates both a positive consistent winners and a negative consistent losers effect, for which past returns would only be a noisy proxy. Consistency may also be a statistical estimate of the inverse of volatility. In addition to analyzing consistency, we investigate whether past positive and past negative returns have distinct implications for future returns. Finally, because prior research on the turn-of-the-year effect suggests that the relations uncovered can be altered by being near the turn of the year, we separately analyze January and December from the rest of the year.

The finance literature shows 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 nonoverlapping past return horizons to isolate these effects.

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

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

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

The pair $t-t2$, $t-t1$ takes on the value $t-1$, $t-1$ when it proxies for the one-month reversal discovered by Jegadeesh (1990). Kaul and Nimalendran (1990), Asness (1995), Lo and MacKinlay (1988), Boudoukh et al. (1994), Jegadeesh and Titman (1995), and Ahn et al. (2000) argue that a significant component of short-term return reversals is driven by liquidity effects or microstructure biases such as bid–ask bounce. Since the reversal may be due to bid–ask bounce and related liquidity effects, we exclude this horizon in some tests. We define being a consistent winner at the one-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 one-year return, which is the momentum effect of Jegadeesh and Titman (1993). We employ the prior year as a ranking period since Moskowitz and Grinblatt (1999) show that one-year individual stock momentum is the strongest among a host of past return variables and remains significant even after accounting for industry effects. In addition, many studies, including those of Fama and French (1996) and Carhart (1997), focus on the one-year effect, and others, including Grundy and Martin (2001), also find the one-year effect to be the strongest ranking horizon for individual stocks. Skipping a month in forming the past one-year return eliminates a potential market microstructure bias and makes the regressor relatively orthogonal to the past one-month return regressors used. The return consistency dummies here test whether the information about expected returns contained in the past one-year of price movements is more complex than past empirical research seems to indicate. The one-year winner consistency dummy is one if the monthly return of the stock was positive in at least eight of the one-year horizon's 11 months, while the loser consistency variable is one if the monthly return was negative in at least eight of the past 11 months.

When $t-t2$, $t-t1$ is $t-36$, $t-13$, we are analyzing the marginal effect of the past three-year return, which is the long-term reversal effect studied by DeBondt and Thaler (1985). As before, skipping a year generates orthogonality with the regressors at other horizons. Consistent winners are stocks with positive returns in 15 of the 23 months from $t-36$ to $t-13$, while consistent losers are stocks with negative returns in at least 15 of these 23 months. This definition of consistency has approximately the same p-values for its tails as the eight of 11 criterion for one-year consistency. Given equal probability of a positive or negative return in any month, the probability of a firm experiencing at least eight of 11 positive return months (or 15 of 23) is approximately 10% under a binomial distribution. Hence, the eight of 11 and 15 of 23 criteria, while arbitrary, were chosen because they capture the top decile of consistent performance under the null.

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, 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). It is designed to hedge out the expected return of stock j, except for the marginal effect of stock j's past pattern of returns.

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 of equity plus deferred taxes and investment tax credits from June of the most recent prior fiscal year divided by size. 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.[2] Within each of the 25 groupings, we 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 two-digit SIC industry groupings of Moskowitz and Grinblatt (1999). Hence, $R_t^{\mathrm{B}}(j)$ 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.

[2] 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.

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. Including market beta, size, 12-month past industry return, one-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.

2.2. Summary statistics

Panel A of Table 1 reports the time series averages of the cross-sectional means (both equal and value weighted) 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.)

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 one- and three-year consistent winners and losers dummies have averages that are above 10% and below 10%, respectively, with the deviation from 10% larger at the three-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 rank percentiles of the stocks' size, BE/ME ratio, turnover, and institutional ownership. Averages are reported separately for stocks in decile 1 (past losers), the middle eight past-return deciles, and decile 10 (past winners).

Note that, except for the three-year horizon, stocks in deciles 1 and 10 tend to be of smaller size and BE/ME, and at all horizons, have higher turnover than stocks in the middle eight deciles. It is not surprising that high turnover is associated with large absolute returns. The size and BE/ME comparisons at the three-year horizon are particularly affected by the fact that extreme long-term returns can substantially alter a stock's market capitalization.

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 one-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 a market cap percentile of 89.41, a BE/ME percentile of 44.99, 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 a market cap percentile of 70.41, a BE/ME percentile of 40.56, a turnover percentile of 62.97, and an

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, $r^{\mathrm{L}}_{-t2:-t1}(j)=\min(0,r_{-t2:-t1}(j))$; and dummies for whether the stock was a consistent winner ($D^{\mathrm{CW}}_{-t2:-t1}$) or loser ($D^{\mathrm{CL}}_{-t2:-t1}$) over the $t-t2:t-t1$ horizon. If the stock had a positive return last month, $D^{\mathrm{CW}}_{-1:-1}=1$; $D^{\mathrm{CW}}_{-12:-2}=1$ (or ($D^{\mathrm{CL}}_{-12:-2}=1$)) if the stock exhibited positive (negative) returns in at least eight of the one-year horizon's 11 months; $D^{\mathrm{CW}}_{-36:-13}=1$ (or $D^{\mathrm{CL}}_{-36:-13}=1$) if the stock exhibited positive (negative) returns in at least 15 of the three-year horizon's 23 months. Also reported are summary statistics on size (market capitalization), book-to-market equity (BE/ME), trading turnover, and percentage of outstanding shares that are institutionally owned. Panel B reports summary statistics on three sets of decile portfolios formed from past one-month, past one-year, and past three-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
$r^{\mathrm{L}}_{-1:-1}$	−0.0404	0.0649	−0.0264
$D^{\mathrm{CW}}_{-1:-1}$	0.4950	0.4723	0.5472
$r_{-12:-2}$	0.1405	0.4837	0.1921
$r^{\mathrm{L}}_{-12:-2}$	−0.1083	0.1679	−0.0438
$D^{\mathrm{CW}}_{-12:-2}$	0.1353	0.3201	0.2179
$D^{\mathrm{CL}}_{-12:-2}$	0.0724	0.2436	0.0349
$r_{-36:-13}$	0.3764	0.9482	0.5393
$r^{\mathrm{L}}_{-36:-13}$	−0.1085	0.1900	−0.0285
$D^{\mathrm{CW}}_{-36:-13}$	0.1849	0.3808	0.3680
$D^{\mathrm{CL}}_{-36:-13}$	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
Turnover[a]	0.6176	3.4147	0.1380
Institutional ownership[b]	25.21%	20.99%	44.48%

Table 1. (*Continued*)

		Time-series average of cross-sectional statistics **Panel B: Decile portfolios**					
		Size rank (%)	BE/ME rank (%)	Turnover[a] rank (%)	Inst. own.[b] rank (%)	CW (%)	CL (%)
	Past one-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 one-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 three-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

[a] Turnover is defined separately for NYSE-AMEX and NASDAQ stocks due to different conventions in recorded volume on the exchanges. The turnover numbers are scaled by the means for each 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.

[b] Calculated from January 1981 onward, when data became available.

institutional ownership percentile of 59.05. Differences in these percentiles highlight 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 one-month past return horizon, we are simply classifying whether the prior month's return was positive or negative. Hence, the percentages for consistent winners and losers sum to one.

3. Results from Fama-MacBeth cross-sectional regressions

Table 2 reports the time series average from August 1966 to July 1995 of the monthly coefficients from the cross-sectional regression in Eq. (1) along with Fama and MacBeth (1973) time-series t-statistics. 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.

The column labels identify whether the coefficients are averaged over all months, Januaries only, February–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 $r_{-36:-13}$, show a strong one-month reversal effect, a weaker one-year momentum effect, and a still weaker three-year reversal effect, respectively, both when averaging the coefficients over all months and when averaging only from February to November. 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 the case for all months as well as February–November.

Hong et al. (2000) and Lee and Swaminathan (2000) show 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 shown 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. 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.

3.1. Winner consistency

One of the more striking findings is that 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, consistent winners outperform other stocks, ceteris paribus. At the one-year horizon,

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 month 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, $r^{\mathrm{L}}_{-t2:-t1}(j)=\min(0, r_{-t2:-t1}(j))$. Also included are consistent winner and loser dummies, $D^{\mathrm{CW}}_{-t2:-t1}$ and $D^{\mathrm{CL}}_{-t2:-t1}$, respectively. If the stock had a positive return last month, $D^{\mathrm{CW}}_{-1:-1}=1$; $D^{\mathrm{CW}}_{-12:-2}=1$ (or $D^{\mathrm{CL}}_{-12:-2}=1$) if the stock exhibited positive (negative) returns in at least eight of the one-year horizon's 11 months; $D^{\mathrm{CW}}_{-36:-13}=1$ (or $D^{\mathrm{CL}}_{-36:-13}=1$) if the stock exhibited positive (negative) returns in at least 15 of the three-year horizon's 23 months. The functional form of the month t cross-sectional regression is,

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

where $\tilde{r}_t(j)$ is stock j's return in month t, and $\tilde{R}^{\mathrm{B}}_t(j)$ 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)
$r^{\mathrm{L}}_{-1:-1}$	−0.0764	−0.2189	−0.0606	−0.0921
	(−9.63)	(−6.79)	(−7.19)	(−4.20)
$D^{\mathrm{CW}}_{-1:-1}$	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)
$r^{\mathrm{L}}_{-12:-2}$	0.0113	−0.0725	0.0170	0.0440
	(2.97)	(−3.57)	(4.62)	(4.72)
$D^{\mathrm{CW}}_{-12:-2}$	0.0046	0.0126	0.0042	0.0017
	(5.80)	(2.61)	(5.30)	(0.67)
$D^{\mathrm{CL}}_{-12:-2}$	−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)
$r^{\mathrm{L}}_{-36:-13}$	−0.0052	−0.0537	−0.0025	0.0159
	(−2.04)	(−3.91)	(−1.02)	(2.31)
$D^{\mathrm{CW}}_{-36:-13}$	0.0014	0.0040	0.0011	0.0010
	(2.73)	(1.93)	(2.03)	(0.63)
$D^{\mathrm{CL}}_{-36:-13}$	−0.0007	0.0108	−0.0015	−0.0036
	(−0.80)	(2.06)	(−1.78)	(−1.22)

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 as a statistical proxy for a lower (constant) variance stock. Rather, it reflects a more complex past returns effect.

We can speculate about the potential source of the consistency effect. For example, Grinblatt and Han (2002) argue that "…'consistent' winning (or 'consistent losing') stocks necessarily have investors who acquired the stock at a basis below the current price—thus experiencing a capital gain (or, in the case of consistent losers, a capital loss)." In their model, such aggregate gains (or losses) cannot be undone by arbitrageurs and lead to reference price updates that revert to fundamentals. This generates mean reversion in the spread between the equilibrium price of a stock and its fundamental value, and, as a consequence, momentum. In Watkins (2002), firms have identical future cash flows but unknown discount rates. Investors have asymmetric information about these discount rates. In a sequential learning model, firms that have experienced consistent price increases tend to be those experiencing dissemination of their low discount rate type and vice versa. Both the Grinblatt and Han (2002) and Watkins (2002) models point to a consistent winners and a consistent losers effect. The absence of a consistent losers effect in our sample, rather than being a rejection of these models, may simply highlight the important price effects of tax-loss trading, which probably apply more to consistent losers. Overlaying tax-loss trading effects on both of these models could generate a consistency effect only in winning stocks. It is worth noting here that Watkins (2002), using CRSP monthly data from 1927 on, shows both a winner and a loser consistency effect. It is difficult to assess whether his findings, which are based on raw returns, would stand up to the controls we use.

3.2. Seasonal patterns and tax-loss selling

The seasonal pattern in Table 2 is also particularly interesting, with both January return coefficients being negative for the one-year variables. Jegadeesh and Titman (1993) identify positive profits for momentum strategies in every month except January, for which they show significant negative profits, and find stronger momentum profits in April, November, and December. They suggest that the negative January profits from a momentum strategy are 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 one-year stock returns (as well as control for one-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.

Can the seasonal pattern in the coefficients reported in Table 2 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 relatively little evidence of a December effect for stock returns. However, Table 2 shows a significant December persistence effect for both one- and three-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 reversals in January. The observed seasonal pattern in losing stocks, both over the one- and three-year past return horizons, as represented by the sums of the coefficients on the pair $r_{-12:-2}$ and $r^{\mathrm{L}}_{-12:-2}$ and on the pair $r_{-36:-13}$, $r^{\mathrm{L}}_{-36:-13}$, exhibit this 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. 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. The coefficient on the past winning returns over both the one- and three-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 three-year past return horizon). This coefficient pattern argues for deferral of large tax-related December net sales in the aggregate when only a few investors experience a large capital gain in the stock. On the other hand, being a consistent winner in December is more indicative of a large number of investors looking at the stock as a winner at the turn of the year. To the extent that a significant fraction of these investors need the gain realization to take advantage of a loss, we would expect a lower coefficient on the consistent winners dummy in December.

The interpretation of the consistent winners coefficient in December hinges on the existence of a degree of relative illiquidity in stock markets at the turn of the year, so that tax-related selling can affect prices. Evidence from Table 2 supports 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 $r^{\mathrm{L}}_{-1:-1}$, possibly due to a liquidity effect, are most negative in January and slightly more negative than usual in December.

The prevailing wisdom, since DeBondt and Thaler (1985) and Chopra et al. (1992), is that the three-year reversal is primarily driven by extreme losers. This is certainly the case for January, as DeBondt and Thaler (1985) and Chopra et al. (1992) also note. The January coefficient on $r_{-36:-13}$ is insignificant, indicating the absence of a three-year winner effect on January returns. However, this hypothesis does not apply to the rest of the year. From February through November there is no difference in the impact of past three-year positive and past three-year negative returns, as evidenced by the insignificant coefficient on $r^{\mathrm{L}}_{-36:-13}$. In addition, the sum of the December three-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 three-year losers coefficient in December is indicative of year-end tax-loss selling.

DeBondt and Thaler (1985, 1987) and Chopra et al. (1992) claim long-term 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), Ball and Kothari (1989), and Fama and French (1996) argue that rational time-variation in expected returns can explain these reversals. By separating long-term reversals from other past return effects and using hedged returns to account for confounding return premia, we provide a more powerful test of the tax-loss selling hypothesis.

3.3. The relation between past return horizons

Recent literature posits a link between the effects of various past return horizons. For instance, Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999) all provide models that tie intermediate-term momentum to long-term reversals under various theories of irrational investor behavior. Hong et al. (2000), Lee and Swaminathan (2000), and Jegadeesh and Titman (2001) claim that such a link exists in the data. However, Jegadeesh and Titman (2001), despite showing that the profits earned from momentum stocks dissipate by the end of a five-year holding period, 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.

By analyzing nonoverlapping return horizons simultaneously, and carefully controlling for confounding return premia, our study provides a cleaner test of the potential link between momentum and reversals. If the one-year past returns effect determines the three-year past returns effect, then intermediate-term momentum is probably an overreaction to past news. This would considerably limit the set of valid theories that could explain these phenomena. 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 unreported results, 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 are unrelated.

3.4. Comparing winner consistency effects with momentum and reversals

Table 2 indicates that being a consistent winner enhances average returns. To assess the economic relevance of being a consistent winner, and to facilitate comparisons with the pure momentum and reversal effect, Table 3 reports average

Table 3
The economic importance of winner consistency
Stocks are ranked each month by past returns and grouped into rank-based decile portfolios, with decile 10 having the highest past 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 over the August 1966 to July 1995 time period. The first five columns report value-weighted results and the next five equal-weighted results. The first column reports the time-series average return of all stocks across all past returns and the next four columns report the time-series average of each of the first and last two return deciles. Average profits are reported for all months, for the month of January only, February–November, and December only. Panel A ranks stocks based on their past one-year return from month $t-2$ to $t-12$, Panel B ranks stocks based on their past three-year return from month $t-13$ to $t-36$. Each portfolio is then broken down into those stocks that were not consistent winners (defined as fewer than eight out of 11 positive past return months in Panel A and fewer than 15 out of 23 positive past return months in Panel B), and the return on the portfolio of these stocks only (where the portfolio is re-weighted to sum to one) is reported. In a similar manner profits are reported for the past return deciles containing only consistent winners defined in Panel A (Panel B) as eight (15) or more and nine (18) or more positive return months out of the past 11 (23).

	Past return decile portfolios									
	Value-weighted					Equal-weighted				
	All	1	2	9	10	All	1	2	9	10
Panel A: Past one-year effect and winner consistency										
All	0.0003	−0.0018	−0.0010	0.0031	0.0054	0.0010	−0.0018	−0.0011	0.0044	0.0060
Jan.	0.0014	0.0070	0.0069	−0.0001	−0.0059	0.0006	0.0004	−0.0009	−0.0128	−0.0133
Feb.–Nov.	−0.0001	−0.0026	−0.0017	0.0032	0.0059	0.0012	−0.0015	−0.0008	0.0057	0.0069
Dec.	0.0025	−0.0017	−0.0012	0.0047	0.0081	0.0002	−0.0058	−0.0037	0.0084	0.0154
Non-consistent winner stocks only										
All	0.0001	−0.0019	−0.0011	0.0029	0.0041	0.0005	−0.0018	−0.0011	0.0041	0.0045
Jan.	0.0019	0.0070	0.0068	0.0013	−0.0034	0.0021	0.0005	−0.0009	−0.0112	−0.0111
Feb.–Nov.	−0.0003	−0.0026	−0.0018	0.0028	0.0044	0.0005	−0.0015	−0.0008	0.0052	0.0049
Dec.	0.0024	−0.0033	−0.0018	0.0050	0.0069	−0.0010	−0.0058	−0.0036	0.0083	0.0146
Consistent winner stocks with at least 8 *out of* 11 *past positive returns only*										
All	0.0016	0.0059	0.0022	0.0042	0.0058	0.0059	0.0017	0.0012	0.0063	0.0091
Jan.	−0.0027	0.0013	−0.0007	−0.0076	−0.0072	−0.0125	−0.0058	−0.0027	−0.0144	−0.0117
Feb.–Nov.	0.0018	0.0039	0.0010	0.0051	0.0063	0.0073	0.0026	0.0012	0.0082	0.0102
Dec.	0.0032	0.0288	0.0146	0.0083	0.0090	0.0114	-0.0009	0.0016	0.0089	0.0176

Consistent winner stocks with at least 9 *out of* 11 *past positive returns only*										
All	0.0039	−0.0010	−0.0013	0.0049	0.0080	0.0072	−0.0004	−0.0009	0.0064	0.0099
Jan.	−0.0046	−0.0028	0.0017	−0.0016	−0.0061	−0.0156	−0.0021	−0.0013	−0.0127	−0.0143
Feb.–Nov.	0.0046	−0.0009	−0.0016	0.0060	0.0082	0.0086	−0.0007	−0.0012	0.0083	0.0107
Dec.	0.0049	−0.0015	0.0001	0.0004	0.0079	0.0124	−0.0015	−0.0004	0.0057	0.0196
Panel B: Past three-year effect and winner consistency										
All	0.0003	0.0015	0.0000	0.0012	−0.0005	0.0010	−0.0003	−0.0014	0.0013	−0.0011
Jan.	0.0014	0.0286	0.0209	−0.0021	−0.0084	0.0006	0.0090	0.0045	−0.0085	−0.0102
Feb.–Nov.	−0.0001	−0.0006	−0.0016	0.0013	0.0000	0.0012	−0.0009	−0.0018	0.0022	−0.0007
Dec.	0.0025	−0.0033	−0.0043	0.0029	0.0013	0.0002	−0.0040	−0.0043	0.0017	0.0030
Non-consistent winner stocks only										
All	0.0006	0.0016	0.0001	−0.0003	−0.0023	0.0010	−0.0003	−0.0014	0.0008	−0.0025
Jan.	0.0057	0.0285	0.0209	−0.0002	0.0011	0.0023	0.0089	0.0045	−0.0071	−0.0080
Feb.–Nov.	−0.0001	−0.0006	−0.0016	−0.0003	−0.0030	0.0010	−0.0009	−0.0018	0.0015	−0.0024
Dec.	0.0018	−0.0035	−0.0043	0.0002	−0.0018	−0.0006	−0.0041	−0.0043	0.0011	0.0010
Consistent winner stocks with at least 15 *out of* 23 *past positive returns only*										
All	0.0000	−0.0055	−0.0034	0.0019	0.0001	0.0004	−0.0038	−0.0029	0.0024	0.0002
Jan.	−0.0069	−0.0021	−0.0017	−0.0006	−0.0098	−0.0091	−0.0036	−0.0073	−0.0001	−0.0115
Feb.–Nov.	0.0000	−0.0068	−0.0044	0.0019	0.0005	0.0011	−0.0049	−0.0030	0.0029	0.0009
Dec.	0.0071	0.0153	0.0093	0.0032	0.0063	0.0039	0.0192	0.0079	−0.0008	0.0061
Consistent winner stocks with at least 18 *out of* 23 *past positive returns only*										
All	−0.0018	0.0021	0.0013	−0.0007	0.0000	−0.0009	0.0022	0.0013	0.0005	−0.0004
Jan.	−0.0173	0.0000	0.0000	−0.0230	−0.0143	−0.0233	0.0000	0.0000	−0.0248	−0.0224
Feb.–Nov.	−0.0009	0.0026	0.0016	0.0017	0.0011	0.0003	0.0027	0.0017	0.0028	0.0005
Dec.	0.0027	0.0000	0.0000	−0.0078	0.0043	0.0114	0.0000	0.0000	0.0002	0.0145

monthly returns of investment portfolios constructed on the basis of past returns and winner consistency. First, we sort firms into decile portfolios based on their past returns and then on the number of winning months. Columns correspond to the past return decile portfolios, with decile 10 having the highest past return. Rows correspond to three classifications of the number of positive past return months and three seasons (January, February–November, and December). The left-hand side of the table reports value-weighted results and the right-hand side equal-weighted results. Panel A reports results for the one-year past return horizon and Panel B reports results for the three-year past return horizon.

Since consistency will only affect the extremes, we report results only for deciles 1, 2, 9, and 10. Attempting inferences from past return portfolios 3–8 is a futile exercise, since few consistent winning firms exist in these portfolios. Similarly, any sensible analysis of this table should focus on numbers that correspond to well-diversified portfolios. For instance, the number of consistent winners in deciles 1 and 2 is negligible. Also, reporting on levels of consistency that are nearly impossible to achieve makes little sense. In Panel A, for example, hardly any firms experience at least ten (of a possible 11) positive past return months, even in past return deciles 9 and 10. The same caveat applies to certain levels of consistency in Panel B, as simple combinatorics would suggest.

Table 3 Panel A, which compares consistency and intermediate-horizon momentum, suggests that consistency is as important as the past return per se. The first row of this panel presents the pure momentum effect. Here, equal-weighted portfolios 9 and 10 earn hedged returns of 44 and 60 basis points per month, respectively (31 basis points and 54 basis points per month, respectively, when value weighting). Different rows in this panel break these numbers down by the number of winning months. Focusing first on decile 10 firms, we note that (on an equal-weighted basis) 67% of the 60 basis-point hedged return comes from firms that are not consistent winners, while 33% comes from consistent winning firms, defined to be firms with at least eight positive monthly returns within months $t-2$ to $t-12$. Also, 13% of the return is derived from extremely consistent winning firms, those with at least nine positive monthly returns within these months. The firms in equal-weighted portfolio 10 that are not consistent winners earned 45 basis points per month, the consistently winning firms earned 91 basis points per month, and the extremely consistent winning firms in decile 10 earned 99 basis points per month.

The regression coefficient on $D^{\mathrm{CW}}_{-12:-2}$ in Table 2 indicates that being a consistent winner over the past year adds 46 basis points per month to a return. Table 3 Panel A suggests that being a consistent winner enhances the performance of stocks within equal-weighted decile 10 by 46 basis points per month, with the spread increasing to 54 basis points per month when we focus on approximately the 13% most consistent stocks, approximately doubling the past return effect.

The numbers are approximately the same if we focus only on February–November, whether equal weighting or value weighting. Because the excellent December performance of these high return firms (overall, as well as in the three subcategories of firms) slightly outweighs their poor performance in January, each of the decile 10 numbers goes up by four to nine basis points if January and December are excluded.

The spreads between the hedged returns of consistent winning firms and firms that are not consistent winners are less dramatic in the decile 9 past return portfolio. They are 30 basis points per month when we exclude January and December and 22 basis points per month over all months.

In comparison with the equal-weighted numbers above, value weighting reduces the additional return enhancement to momentum generated by being a consistent winner, but only moderately from February–November. The seasonal difference arises because the large-cap firms in deciles 9 and 10 that are not consistent winners exhibit either surprisingly modest or no January reversals relative to their benchmark. We are reluctant to draw conclusions from this, particularly for any average return associated with a single month.

On an equal-weighted basis, the February–November hedged returns of stocks with at least eight of the 11 relevant months being positive is 73 basis points per month, while with nine or more months being positive, the hedged return modestly jumps to 86 basis points per month. These numbers are clearly of the same order of magnitude as the past returns effect per se.

Table 3 Panel B tells a similar story for the long-term reversal effect. Outside of January, there is little reversal in equal-weighted portfolio 10, unless one separates out the consistent winners. A modest reversal from February to November does exist, but only for the 59% of stocks that are not consistent winners. The latter stocks earn a February–November hedged return of −24 basis points per month (−30 basis points per month when value weighted). This is 33 basis points per month less than the stocks in the same portfolio with at least 15 positive returns in the relevant 23 months (59% of portfolio 10) and 29 basis points per month less than the 7% of stocks in the same portfolio with at least 18 positive returns in the relevant 23 months. In decile 9, the spread between consistent winning stocks and stocks that are not consistent winners is about one-half this size.

4. Economic significance of the past expected-return relation

To further examine the economic importance of the relation between the past pattern of returns and expected returns, we form trading strategies based on the insights from the previous regressions. 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 we use average coefficients from the appropriate sample of months (as discussed below) to weight the regressor values. Decile portfolios either equal or value weight the stocks within each decile rank.

4.1. Profitability and risk of trading strategies from stock rankings

Panel A of Table 4 reports average monthly hedged returns along with annualized standard deviations for each corresponding decile portfolio (both equal and value

Table 4
Economic significance of the relation between past and expected returns

Average monthly returns and annualized standard deviations (σ) 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–November coefficients for February–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 one-month past return regressors to rank stocks. Panel C uses only the four regression coefficients corresponding to one-year past return regressors to rank stocks, and Panel D uses only the four regression coefficients corresponding to three-year past return regressors to rank stocks. Also reported in each panel are the equal- and value-weighted profits from ranking systems that ignore (zero out) the coefficients on the consistent winners dummy variables denoted as NCW.

	Decile portfolios										10^{-1} (t-stat.)
	1	2	3	4	5	6	7	8	9	10	
Panel A: All regressors											
(*Equal-weighted*)											
All	−0.0065	−0.0046	−0.0026	−0.0007	0.0009	0.0016	0.0027	0.0041	0.0076	0.0215	0.0280
σ	0.0518	0.0428	0.0430	0.0404	0.0375	0.0328	0.0336	0.0325	0.0462	0.1052	(12.85)
NCW	−0.0066	−0.0045	−0.0029	−0.0011	0.0011	0.0017	0.0029	0.0036	0.0069	0.0196	0.0262
(*Value-weighted*)											
All	−0.0047	−0.0035	−0.0023	−0.0012	0.0012	0.0012	0.0029	0.0051	0.0062	0.0092	0.0139
σ	0.0693	0.0456	0.0465	0.0520	0.0486	0.0464	0.0490	0.0532	0.0693	0.1104	(6.48)
NCW	−0.0048	−0.0038	−0.0022	−0.0010	0.0007	0.0010	0.0025	0.0049	0.0050	0.0078	0.0126
Panel B: Exclude past one-month regressors											
(*Equal-weighted*)											
All	−0.0055	−0.0039	−0.0023	−0.0002	0.0011	0.0019	0.0027	0.0043	0.0056	0.0113	0.0168
σ	0.0587	0.0444	0.0444	0.0385	0.0347	0.0354	0.0344	0.0414	0.0437	0.0984	(7.77)
NCW	−0.0053	−0.0041	−0.0031	−0.0002	0.0008	0.0020	0.0026	0.0034	0.0055	0.0094	0.0147

(*Value-weighted*)											
All	−0.0051	−0.0035	−0.0018	−0.0002	−0.0004	0.0015	0.0025	0.0026	0.0040	0.0061	0.0111
σ	0.0796	0.0606	0.0598	0.0516	0.0549	0.0500	0.0630	0.0576	0.0520	0.1016	(4.94)
NCW	−0.0052	−0.0035	−0.0019	0.0000	0.0003	0.0015	0.0008	0.0020	0.0041	0.0046	0.0098
Panel C: Past one-year regressors only											
(*Equal-weighted*)											
All	−0.0050	−0.0038	−0.0026	−0.0012	−0.0001	0.0017	0.0036	0.0048	0.0058	0.0110	0.0160
σ	0.0480	0.0410	0.0438	0.0412	0.0383	0.0383	0.0434	0.0442	0.0452	0.0843	(8.66)
NCW	−0.0049	−0.0039	−0.0023	−0.0007	−0.0001	0.0016	0.0034	0.0047	0.0061	0.0091	0.0140
(*Value-weighted*)											
All	−0.0021	−0.0018	−0.0014	−0.0011	−0.0007	0.0002	0.0026	0.0040	0.0034	0.0049	0.0071
σ	0.0680	0.0553	0.0602	0.0460	0.0519	0.0518	0.0658	0.0512	0.0589	0.0865	(3.63)
NCW	−0.0021	−0.0016	−0.0011	−0.0006	−0.0001	−0.0007	0.0015	0.0040	0.0041	0.0037	0.0058
Panel D: Past three-year regressors only											
(*Equal-weighted*)											
All	0.0004	0.0003	0.0002	−0.0007	−0.0014	−0.0017	0.0026	0.0027	0.0036	0.0063	0.0059
σ	0.0382	0.0381	0.0472	0.0540	0.0600	0.0597	0.0693	0.0586	0.0600	0.0866	(3.52)
NCW	0.0003	−0.0001	−0.0004	−0.0003	−0.0016	−0.0011	0.0016	0.0037	0.0025	0.0051	0.0048
(*Value-weighted*)											
All	0.0008	0.0005	0.0001	−0.0008	0.0009	−0.0012	0.0017	0.0016	0.0033	0.0026	0.0017
σ	0.0474	0.0402	0.0513	0.0577	0.0681	0.0605	0.0662	0.0616	0.0855	0.0931	(1.02)
NCW	0.0011	0.0008	0.0002	−0.0015	0.0009	0.0001	0.0020	0.0020	0.0021	0.0023	0.0012

weighted). It also reports the spread between the average returns of deciles 10 and 1 along with t-statistics in the far right column. The deciles are obtained using three sets of coefficients, with the January coefficients from Table 2 used for January rankings, the February–November coefficients for ranking stocks from February through November, and the December coefficients for ranking stocks in December. The first two rows of Table 4 Panel A report, respectively, the average hedged returns and standard deviations of hedged returns of equal-weighted decile portfolios formed from this dynamic trading strategy. The fourth and fifth rows represent corresponding returns and standard deviations for monthly rebalanced value-weighted portfolios.

The returns from the decile portfolios are strictly monotonic. In comparison with their benchmarks, the decile 1 portfolio loses 65 basis points per month on average when equal weighted and loses 47 basis points per month on average when value weighted. Relative to its benchmark, the decile 10 portfolio earns 215 basis points per month on average when equal weighted and 92 basis points per month on average when value weighted. Hence, controlling for size, book-to-market, and industry, the best-ranked equal-weighted portfolio outperforms the worst-ranked equal-weighted portfolio by 280 basis points per month, and by 139 basis points per month when deciles 10 and 1 represent value-weighted portfolios. The annualized standard deviations of the hedged returns of the ten decile portfolios is slightly U-shaped, both for the equal- and value-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. The decile 10 portfolios, with hedged return volatilities of 10.52% and 11.04% (equal and value weighted, respectively), are notably more risky than the other nine decile portfolios.

The 280 and 139 basis point per month spreads between decile portfolios 10 and 1 in Panel A could partly be attributed to market microstructure effects. In particular, the past one-month return can be negatively related to the current month return because of bid–ask bounce and related liquidity effects. To avoid any potential microstructure bias, Table 4 Panel B reports decile portfolio performance using a scoring system where the coefficients on the three one-month past return variables are set to zero. The average return spread, at 168 basis points per month (equal weighted) and 111 basis points per month (value weighted), is still rather remarkable. Thus, the impressive profits generated by the strategy in Panel A, while potentially biased upward by market microstructure effects, are mostly due to other factors. Taking out potential contamination from market microstructure biases also does not seem to affect our conclusions about volatility.

To assess the relative economic importance of the one- and three-year horizons, Panels C and D of Table 4 analyze the profitability of the Fama-MacBeth scoring system using only the coefficient estimates on the four one-year horizon variables (Panel C) or the four three-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 equal or value weighted.

A comparison of Panels C and D indicates that the past one-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 three-year horizon strategy, when value-weighting, is only about one-fourth the size of the one-year strategy's profitability. This could be because the three-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 160 basis point spread between deciles 10 and 1. 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.

4.2. The importance of winner consistency

The last section showed that being a consistent winner seems to enhance profitability. This is the case for the momentum and reversal strategies generated by the more complex ranking system here as it was for the simple momentum and reversal strategies studied in Table 3. To demonstrate this, Table 4 reports value- and equal-weighted decile portfolios that exclude consistent winners' criteria (denoted as NCW rows). This corresponds to sorting into decile portfolios using a scoring system with coefficients identical to those in the rest of the corresponding panel, except that the coefficients on all consistent winners' dummy variables are set to zero. In general, the spread between the decile 10 and decile 1 portfolios decline, typically on the order of 10–20 basis points per month. They are similar whether value or equal weighting within the decile portfolios.

The relatively small decline in spreads is not a reflection of the marginal impact of winner consistency, however. A 40–50 basis-point per-month winner-consistency effect can easily generate a 10–20 basis point spread decline in the NCW row. This decline measures a netting of a return effect against a winner consistency effect. Also, the spread decline is diluted in that deciles 10 and 1 have a substantial number of overlapping firms in the All and NCW categories. To gain insight into the marginal impact of winner consistency in a portfolio context, we need to break up the decile portfolios in the non-NCW rows into subportfolios based on winner consistency (provided that each of the subportfolios is reasonably well diversified). Although not reported in a table, the decile 10 effects for the one-year strategy summarize the marginal impact of winner consistency. For Panel C, stocks in the All row with fewer than eight positive returns over the 11-month horizon comprise 19.83% of the value-weighted returns for decile 10 (36.39% of equal-weighted decile 10). For the value-weighted decile 10 portfolio, from February through November, there is no profitability to the one-year strategy with these inconsistent stocks. Despite having a high predicted return, stocks within the decile 10 portfolio that are not consistent winners 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 decile 10 stocks in Panel C that are not consistent winners beat their benchmark by 20 basis points per month when equally weighted. By contrast, a strategy of buying the one-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 winners and other stocks within equal-weighted decile 10. The same lesson applies to the pure three-year strategy, although here, the strategy was not profitable outside of January.

5. Do tax-motivated trades affect the relation between past and expected returns?

Given the strong seasonal patterns observed in Table 2, this section further analyzes the role played by tax-loss trading in the relation between past and expected returns. We first analyze the profitability of the strategy generated by the Fama-MacBeth regressions across seasons and sectors of the economy most likely affected by tax-motivated trades. We then exploit variation in the tax code to study the influence of tax regimes on the profitability of these strategies.

5.1. Turnover, institutional ownership, size, and seasonalities: tax vs. behavioral motivations

Table 5 reports the spread between deciles 10 and 1 within subsamples of stocks, both overall and broken down by season. The scoring system for generating the deciles is identical to the scoring system used in the last table. Panel A 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 cross-sectional correlation with firm size. Lee and Swaminathan (2000) examine NYSE-AMEX traded stocks and find that momentum and subsequent three-year reversals are stronger among stocks with high turnover, mostly driven by the dismal performance of high turnover 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 turnover 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. Due to the dealer system, each NASDAQ trade is generally counted twice and sometimes more, exaggerating trading turnover relative to the traditional exchanges. Therefore, we separately report results for NYSE/AMEX and NASDAQ stocks. The breakpoints for the turnover quintiles are exchange specific. In general, the investment strategies we formulate generate higher returns among high turnover stocks, consistent with Lee and Swaminathan (2000). However, the added profitability among high turnover NASDAQ stocks is due to performance at the turn of the year. Among NASDAQ

Table 5
Profits across sectors of the market
Profits from the stock ranking system of Table 2 are reported below across various sectors of the market. 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–November coefficients for February–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. Profits are reported for stock ranking systems that employ all coefficients, exclude those associated with one-month returns, employ only the one-year past return coefficients, and employ only the three-year past return coefficients, respectively. Panel A reports profits for the lowest and highest quintile of stocks based on trading turnover (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 B reports 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 (using NYSE market capitalization breakpoints). Profits are reported for all months, January only, February–November only, and December only.

	Lowest quintile				**Highest quintile**			
	All	Ex. one-month	One-year only	Three-year only	All	Ex. one-month	One-year only	Three-year only
Panel A: Across turnover quintiles								
(*NYSE-AMEX only*)								
All	0.0116	0.0043	0.0043	0.0001	0.0154	0.0146	0.0100	0.0007
	(0.106)	(0.099)	(0.104)	(0.090)	(0.181)	(0.175)	(0.157)	(0.151)
Jan.	0.0241	0.0193	0.0103	0.0174	0.0564	0.0442	0.0168	0.0407
	(0.178)	(0.112)	(0.130)	(0.088)	(0.342)	(0.320)	(0.205)	(0.171)
Feb.–Nov.	0.0104	0.0030	0.0043	−0.0022	0.0113	0.0127	0.0092	−0.0031
	(0.099)	(0.099)	(0.102)	(0.088)	(0.148)	(0.153)	(0.152)	(0.138)
Dec.	0.0146	0.0026	−0.0003	0.0047	0.0186	0.0067	0.0142	−0.0032
	(0.070)	(0.092)	(0.111)	(0.107)	(0.209)	(0.165)	(0.170)	(0.206)
(*NASDAQ only*)								
All	0.0176	0.0114	0.0104	0.0016	0.0330	0.0196	0.0125	0.0069
	(0.158)	(0.142)	(0.154)	(0.119)	(0.248)	(0.261)	(0.216)	(0.175)
Jan.	0.0436	0.0175	0.0007	0.0174	0.1277	0.1177	0.0425	0.0352
	(0.286)	(0.270)	(0.224)	(0.197)	(0.399)	(0.541)	(0.330)	(0.247)
Feb.–Nov.	0.0141	0.0097	0.0101	−0.0021	0.0236	0.0075	0.0063	0.0033
	(0.132)	(0.120)	(0.141)	(0.106)	(0.210)	(0.184)	(0.192)	(0.167)
Dec.	0.0206	0.0182	0.0116	0.0169	0.0282	0.0353	0.0313	0.0102
	(0.191)	(0.143)	(0.178)	(0.116)	(0.186)	(0.252)	(0.258)	(0.160)

Table 5. (*Continued*)

	Lowest quintile				**Highest quintile**			
	All	Ex. one-month	One-year only	Three-year only	All	Ex. one-month	One-year only	Three-year only
Panel B: Across institutional ownership quintiles								
(*Smallest* 1/3 *market capitalization*)								
All	0.0224	0.0219	0.0214	−0.0002	0.0151	0.0110	0.0118	−0.0012
	(0.163)	(0.165)	(0.131)	(0.135)	(0.175)	(0.155)	(0.155)	(0.168)
Jan.	0.1021	0.0983	0.0714	0.0534	0.0371	0.0143	0.0065	0.0278
	(0.299)	(0.357)	(0.270)	(0.196)	(0.185)	(0.217)	(0.154)	(0.145)
Feb.-Nov.	0.0132	0.0134	0.0149	−0.0071	0.0118	0.0112	0.0122	−0.0047
	(0.105)	(0.100)	(0.083)	(0.117)	(0.172)	(0.150)	(0.152)	(0.164)
Dec.	0.0267	0.0364	0.0239	0.0180	0.0189	0.0119	0.0002	0.0097
	(0.132)	(0.123)	(0.117)	(0.071)	(0.169)	(0.153)	(0.161)	(0.235)
(*Largest* 1/3 *market capitalization*)								
All	0.0048	0.0058	0.0018	0.0013	0.0085	0.0055	0.0083	0.0020
	(0.164)	(0.153)	(0.153)	(0.135)	(0.120)	(0.113)	(0.114)	(0.093)
Jan.	0.0244	0.0318	0.0208	0.0230	0.0232	0.0263	0.0217	0.0235
	(0.220)	(0.179)	(0.165)	(0.162)	(0.174)	(0.183)	(0.145)	(0.107)
Feb.–Nov.	0.0011	0.0018	−0.0019	0.0000	0.0063	0.0046	0.0062	0.0009
	(0.150)	(0.145)	(0.146)	(0.132)	(0.106)	(0.103)	(0.097)	(0.089)
Dec.	0.0091	0.0211	−0.0012	0.0000	0.0050	−0.0044	−0.0018	−0.0012
	(0.192)	(0.178)	(0.148)	(0.142)	(0.105)	(0.087)	(0.131)	(0.082)

firms, for instance, the enhanced profitability of one-year momentum by high turnover is entirely due to January and December, consistent with year-end tax-loss selling. In December, the high turnover momentum stocks outperform the low turnover momentum stocks. In January the reverse is true, but our one-year strategy becomes a contrarian strategy at that point. Among NYSE-AMEX stocks, the one-year strategy is more profitable on high turnover than low turnover stocks from February to November. While this may imply that other factors besides tax-loss selling contribute to the 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 turnover enhances profitability is so much higher in December. Note also that among both NYSE/AMEX (as with NASDAQ stocks), the high turnover one-year strategy outperforms the low turnover strategy in January. Since the latter strategy is contrarian in January, a low turnover momentum strategy should outperform a high turnover momentum strategy in January.

The salience of December and January to the enhanced profitability of the strategies among high turnover stocks seems inconsistent with Lee and Swaminathan's (2000) behavioral story of a "momentum life cycle." 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 turnover/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. Our findings point to year-end tax-loss selling as a potential alternative to the mysterious role played by turnover in the relation between past returns and expected returns.

To further investigate the role of tax-motivated trading on these profits, Table 5 Panel B studies the spread between value-weighted deciles 10 and 1 across quintiles based on the fraction of a firm's shares held by institutions, as reported by Standard & Poor's, within the smallest and largest third of stocks. Due to data limitations, the analysis here is from 1981 on. Firm size quintiles use NYSE breakpoints. 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.

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

An alternative explanation for the contrasting findings is related to the observation by Grinblatt et al. (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 can reduce 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.

The top and bottom halves of Panel B also indicate that the profitability of the three most profitable investment strategies decreases with firm size. For example, in the second column, which has low institutional ownership, a strategy generated by all coefficients except those associated with the past month earns 201 basis points per month when applied to only the smallest quintile of stocks, but only 58 basis points per month when applied to the largest quintile, most of which is accounted for by January and December.[3] Hence, the stronger influence of past returns on expected returns for small stocks documented by Hong et al. (2000) is at least partly driven by a strong year-end seasonal. Such seasonal patterns are difficult to explain with Hong et al.'s (2000) slow information diffusion theory. 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 can be due to other factors, including slow information diffusion.

5.2. The influence of the tax regime

So far, we have hinted that the strong seasonal pattern in the profitability of these technical trading strategies is driven by tax-motivated trades. Evidence on turnover and institutional ownership is supportive of this conjecture. To test this more directly, we examine how tax regime shifts alter the profitability of our trading strategy.

Poterba and Weisbenner (2001) analyze 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 applied to 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.

We measure the profitability of our value-weighted trading strategy (excluding one-month effects) for two subsamples. First, we analyze 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 $t+1$. Then, we analyze low tax years,

[3] Earlier drafts of this paper observed that similar size distinctions arise when the subsamples are based only on firm size and extend to the entire sample period.

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 1968–1969, 1972–1975, 1981, 1985–1986, 1988–1999 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 run 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 one-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 6 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.

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–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 insignificant to significant 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 Table 6 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,

Table 6

How does tax-loss trading affect the relation between past and expected returns?

Profits are reported from the stock ranking system of Table 2 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 one-month regressors) are used to score stocks, where January coefficients are used for January rankings, February–November coefficients for February–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 past losers in December (due to continuation) and buys past 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 1968–1969, 1981, 1972–1975, 1985–1986, and 1988–1999. The remaining years are low tax years.

Profits:			**August 1966 to December 1999**			
Strategy:			Exclude one-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: Losers (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: Loser (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.

it should show up most strongly among the decile of losing stocks. Because we are excluding the past one-month in formulating the strategy, this corresponds to decile 1 in December and to decile 10 in January. Moreover, this turn-of-the-year pattern across tax regimes should exhibit enhanced profits for those stocks that are most likely held by taxable investors. These would be small-cap stocks with low institutional ownership.

Panels B and C of Table 6 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 Table 6 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 supported by comparisons made across categories. In Table 6 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. Among large cap stocks, institutional ownership only accounts for a three basis point difference in December.

In Table 6 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 tax-loss selling accounts for our findings.

6. Transaction costs and out-of-sample results

Finally, given the large profits associated with our trading strategies based on consistency and tax-related effects, we assess whether the profits generated from these strategies could have persisted because of substantial trading frictions or are a byproduct of data snooping.

6.1. 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. The investor would want to avoid or downweight stocks with particularly high trading costs, notably stocks with low prices and small market capitalizations, and would be more interested in value- than equal-weighted portfolios. The investor also might avoid employing information from the past one-month return due to potential market-microstructure effects.

In our case, restricting the value-weighted portfolios formed in Table 3 to above \$5 stocks is fairly innocuous. For comparison purposes, the left-hand side of Panel A of Table 7 summarizes the same information in Table 3, broken down by season. The left-hand side of Table 7 Panel B repeats the analysis in Panel A, but focuses exclusively on stocks with prices above \$5 at the beginning of the month. As can be seen from the table, the average spread between value-weighted deciles 10 and 1 generally declines, but only slightly. In going from Panels A to B, the decline is four basis points per month for the overall strategy, 11 basis points for the strategy that excludes the prior month, and one basis point with the three-year strategy. With the one-year strategy, 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.

It is instructive to focus on the second column in Panel B in trying to assess whether this is a viable strategy for an investor concerned about trading costs. While 100 basis points per month is impressive, the turnover of the strategy is large. In our final and particularly volatile year, 1999, 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. Trading costs of about 1% are approximately the breakeven costs for this strategy. On the other hand, because of value weighting, the typical dollar invested in a long or a short position is in a stock that is in the 86th percentile of market capitalization (for both the long and the short positions). These stocks have substantially lower trading costs than the average stock. Moreover, the information we use in formulating the strategy that excludes the past month is at least a 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. Since the introduction of decimalization and Internet commissions were not accounted for in this study, these costs may now be even lower. 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.

Table 7

In- and out-of-sample profits from past return patterns

Profits from the stock ranking system of Table 2 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–November coefficients for February–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 estimation period. Profits are reported for stock ranking systems that employ all coefficients, exclude those associated with one-month returns, employ only the one-year past return coefficients, and employ only the three-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. 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 all months, January only, February–November only, and December only.

	In sample August 1966 to July 1995				Out of sample August 1995 to December 1999			
	All	Ex. one-month	One-year only	Three-year only	All	Ex. one-month	One-year only	Three-year only
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)

A significant component of the turnover in the strategy 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 (2002) and Reed (2002) 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 could be almost an order of magnitude too high for value-weighted portfolios.

6.2. *Out-of-sample results*

The scoring system that generates the ranks for the stocks is 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. Sullivan et al. (1999) suggest that calendar effects in stock returns, like the anomalous January effect, can be generated purely by data snooping. If the success of our specification of the regressors was the product of an intensive search for the most marketable (or publishable) trading strategy using past literature as a guide, the results obtained here would not hold for the five years of additional data that became available after the first draft of this paper formulated this trading strategy.

The right-hand side of Table 7 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 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–December 1999, as in the in-sample period. While not all of the out-of-sample numbers exceed their in-sample counterparts, most are economically significant and of similar magnitude. 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.

7. Conclusion

The past pattern of returns seems to matter as much as the magnitude of the past return for the cross-section of expected returns. Most notably, we find that consistency of past winning stocks has a substantial impact on the cross-section of returns. In cross-sectional regressions, the marginal impact of consistent winners at all horizons is positively related to future average returns. Almost all of the consistent winners' coefficients are statistically significant. Moreover, being a consistent winner is economically important. For the typical firm, being a consistent winner can double the return premium associated with a firm belonging to the top momentum decile.

Being a consistent loser appears to be irrelevant to the cross-section of returns. We can only speculate about the reasons for this. For example, tax-loss selling is likely to play a larger role for consistent losers than consistent winners. It is possible that tax-loss selling is masking or offsetting whatever behavioral phenomenon contributes to a consistency effect in stock returns.

Although numerous studies attempt to analyze the tax-loss selling hypothesis, most focus on stock returns in January and do not examine variations in the tax code or the role played by tax-loss selling in the profitability of momentum and reversal strategies. We show that there are strong December effects in stock returns. Moreover, our argument that these seasonalities are related to tax-loss trading is buttressed by our analysis of how tax regimes affect the relation between past and expected returns. We find statistically significant profits from technical trading strategies only in high tax regimes, including the strong seasonal effects. Furthermore, the subcategories of stocks on which these technical trading strategies work best (e.g., small, low institutional ownership stocks) are also those most susceptible to tax-loss trading.

Finally, we examine these novel findings in the context of recent behavioral theories for past return predictability. Current theory is challenged by many of the results we uncover. For instance, we find that at least part of the intermediate-term momentum and long-term reversal 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, as suggested by recent theory. The strongest link seems to be driven by end-of-year tax-loss selling. Certainly, future theory should consider the relevance and importance of both consistency and seasonal effects.

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