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Abstract

We show that the level of interest rates determines the magnitude of mispricing at the turn of the tax year, as investors face the trade-off between selling a temporarily-depressed stock this year and selling next year, but delaying tax implications by one year. Interest rates do explain the predictable variation in US returns and selling behavior around the turn of the year. Similar results in the UK provide out-of-sample confirmation, as tax and calendar years differ. Moreover, part of the variation in the risks and abnormal returns of size, value, and momentum factors can be linked to tax-motivated trading.

Key words: tax-loss harvesting, January effect, downward-sloping demand curves
JEL classification: G11, G12

Previous research has argued that a tax-motivated seller should sell losers early and hold on to winners under the assumption that tax-selling behavior does not create distortions in market prices (Constantinides (1983, 1984)). However, recent research has argued that such tax-selling behavior at the turn of the year does generate seasonality in the cross-section of stock returns, whose magnitude depends on the level of the capital gains tax rate (in particular, Poterba and Weisbenner (2001) and Grinblatt and Moskowitz (2004)). We build on these results and show that (because interest rates determine the present value of the tax gain/loss) the impact of tax-motivated selling also depends on the level of interest rates. In the presence of downward sloping demand curves for stocks and limits to arbitrage, both interest rates and capital gains tax rates drive the extent to which past losers trade at a temporary low price at the end of the year.

Our framework suggests that the magnitude of the January rebound return because of tax-loss selling at the end of the year should vary both in the cross-section and in the time-series. The cross-section of average January returns should vary with a stock's capital gains overhang, defined as the ratio of the cumulative gain since the stock's purchase to its current price.² For a given level of capital gains overhang, time-series variation in the January rebound return should depend on macroeconomic variables: the capital gains tax rate (which determines the magnitude of the tax payment or credit) and the interest rate (which drives the personal benefit/cost of delaying that tax payment/credit). In particular, we link the interest-rate component of this time-series variation to the one-year interest rate since the decision to delay the sale of the stock from the last trading day of December to the first trading day of January results in the delay of any tax benefit/cost by one year. Rather than file and receive the tax credit in early January, the investor must wait a year to capture the tax savings.

In summary, while previous literature has shown that variation in capital gains tax rates appears to forecast variation in the degree of selling pressure for loser stocks, we argue that variation in interest rates is at least as important.³ We first provide an exact formulation for the way these two rates drive the stock return seasonal

²The terminology capital gains overhang is standard in this literature (see for example Grinblatt and Han (2005)).

³In our formulation, the tax-selling premium is the amount of January rebound return for a unit spread in capital gains overhang and is a function of interest rates and tax rates. Variation in this premium is primarily due to interest rates. If one were to fix interest rates at their average level over the sample, only allowing tax rates to vary, the resulting variation in the tax-selling premium is roughly one-third of the variation in the premium we document.

caused by tax-motivated selling. We then show that this formulation does a good job describing relevant aspects of the data.

The following example clarifies the intuition behind our idea. Suppose a taxable investor in the 30% tax bracket bought a stock at \$100 several years ago. The stock has declined in value since this purchase and is currently trading at \$4. Selling the stock at \$4 on the last trading day of December would generate a capital loss of \$96 and offer a tax deduction of \$28.80 ($30\% \times \96). Thus, proceeds total \$32.80: \$28.80 from the tax deduction and \$4 from the stock sale.

Alternatively, the investor could wait to sell the stock on the first trading day in January. The decision to wait provides January sales proceeds of \$4 (ignoring the small discounting across the turn of the year), but now the tax benefit will not occur until one year later and thus must be discounted by the one-year rate relevant to this investor, here assumed to be 5%. The total present value of the proceeds from waiting until January now equals \$31.43: \$4 due to the sale and \$27.43 due to the present value of the tax benefit ($30\% \times \$96 / 1.05$). Waiting to sell the stock on the first trading day in January results in a loss of \$1.37 in present value due to the deferral of the tax savings by one year. This analysis makes it clear that the investor would be willing to sell the stock below the \$4 fair value in December, but only to a certain limit.

Assuming that the beginning-of-January price remains at the fair value of \$4, what December price, P , would make the investor indifferent between selling in December versus January? To be indifferent, the proceeds of the sale at the end of the year, $P - 30\% \times (P - \$100)$, must equal the present value of the proceeds from selling the stock at the beginning of next year $\$4 - 30\% \times (\$4 - \$100) / 1.05$. By equating these two values, one finds that the stock can sell as low as \$2.04 implying a \$1.96 discount relative to its fair value. This lower bound limits the extent to which price pressure can drive the stock price down in December and thus limits the magnitude of the January rebound. This lower bound depends on interest rates and capital gains tax rates in addition to the level of the capital loss. Below \$2.04, the investor delays selling the stock, at \$2.04 the investor is indifferent, and anywhere above \$2.04 the investor is better off selling now rather than waiting. In Section 1 we derive an explicit formula based on this example. The formula shows a stock's January rebound return depends on that stock's December capital gains overhang as well as interest and tax rates.

The example above highlights the importance of interest rates in the decision process. Suppose that the interest rate in the previous example were zero. Since

there would be no benefit for accelerating the tax benefit to occur this year rather than the next, the solution for P is clearly \$4. More generally, at very low interest rates, a rational tax-motivated seller tolerates very little mispricing.

We take these predictions to the data. We create a proxy for a stock’s capital gains overhang following the methodology of Grinblatt and Han (2005). Specifically, we use past volume to weight past prices in order to create a proxy for a stock’s tax basis and therefore the capital gains overhang of the marginal seller of the stock. Just as the example above suggests, we show that the ability of this variable to describe cross-sectional variation in average returns at the turn of the year is a function of interest rates and tax rates, which we dub the *tax-selling premium*. This predictability is robust to including controls for various firm characteristics (size, book-to-market, trading volume, and past return patterns) in our regression analysis.

We carefully explore the nature of this documented cross-sectional and time-series variation in expected returns to show that it is consistent with our economic explanation. We find that the majority of the effect occurs in the days surrounding the turn of the year, but this effect is also present on a smaller scale during the entire month of December and even earlier. Though we primarily analyze U.S. data, we also find similar time-series and cross-sectional variation in expected returns in U.K. data during the turn of that country’s *tax* year.⁴ As the U.K. tax year ends in April, we argue that these international results provide strong evidence that our U.S. findings are consistent with a tax-selling explanation.⁵

Moreover, we document that this phenomenon shows up in the trading volume of individual investors. We examine the trading behavior of individual investors using two different methods. First, using the TAQ database, we find that stocks with low capital gains overhang have more selling pressure at the turn of the year than stocks with high capital gains overhang and that this imbalance varies as a function of our tax-selling premium. Our second method directly measures investors’ propensity to sell using the actual trades from the large discount brokerage studied in Odean (1998). We show that not only are investors more likely to harvest capital losses before the turn of the year but also this tendency to accelerate the realization of capital losses is much stronger in the years where interest rates and tax rates are high.

⁴Reinganum and Shapiro (1987) show that after the introduction of capital gains taxes in the U.K., the difference in April returns between winners and losers becomes significantly greater than zero, consistent with a tax-loss selling story. Our empirical contribution is to show that this premium varies with the interest rate as predicted by our formulation.

⁵We thank the editor, Cam Harvey, for this suggestion.

Since these firm-level findings make us confident that the tax-based pricing model is a useful description of average returns at the turn of the year, we then examine the way that tax-based cross-sectional and time-series variation in expected returns affects standard monthly performance attribution regressions. We first show that tax-loss selling effects are also present at the aggregate level. Specifically, we document that the return on the market portfolio in January has a similar predictable component that is a function of interest rates, tax rates, and the market's capital gains overhang. Since this is the case, one might expect that measures of risk can be driven by cross-sectional variation in the covariance of firm-level and market capital gains overhang. We confirm that our tax-selling variables drive the alpha and market beta of a long-short overhang portfolio. Moreover, similar predictable patterns can be found in the Fama-French (1993) and Carhart (1997) factors. These findings have important implications for researchers examining economic stories describing time-variation in the risks and returns of these factors.⁶

In short, our empirical results are consistent with the view that tax-motivated selling in the presence of downward-sloping demand curves results in stock return seasonality (a turn-of-the-tax-year effect) where the extent of the resulting price pressure depends on the level of interest rates and capital gains tax rates. Consequently, our results have a practical implication for those trying to exploit the January effect, as we show that the magnitude of the anomaly should and does vary over time. In years when capital gains overhang is limited, capital gains tax rates are low, and interest rates are also low, one should not expect a large January effect.

This time variation has a related implication. Note that some market commentators have argued that savvy investors must have eliminated the January effect since recent returns to strategies exploiting that phenomenon have been low. However, as interest rates have also been quite low in recent data, we provide an alternative explanation for this recent poor performance. In fact, we show that the time-series variation in the tax-selling premium that we document is not subsumed by the inclusion of a time trend.

Nevertheless, as is the case with other financial anomalies, it is always difficult to explain the reason this inefficiency has not been arbitrated away. We suggest a few explanations for the limits to arbitrage in this case. First, unlike the value and

⁶For example, Chordia and Shivakumar (2002) and Cooper, Gutierrez, and Hameed (2004) forecast returns on momentum strategies with variables that are clearly related to the variables our tax-based approach suggests.

momentum anomalies, the return pattern discussed here cannot be exploited on a regular basis but *at most* only once a year during the turn of the tax year. Hence, arbitrageurs may be reluctant to allocate a significant fraction of their risk capital to exploit this return pattern. Second, most arbitrageurs may not be aware of the time variation in the profitability of the January effect that our analysis documents. Finally, these effects should be stronger in stocks where there are many taxable investors. Presumably, the market for these stocks may be less efficient.

One can also question the reasons investors do not trade earlier in the year to try to avoid the clumping that appears to occur. We argue that investors may naturally display inattention to this decision because it is costly to observe and process information.⁷ This argument is consistent with a growing recent literature that has used investor inattention to understand patterns in financial markets. Reis (2006) develops a model of optimal inattention for a consumer who faces a cost of observing additive income, such as labor income. Gabaix and Laibson (2002) model the cost of observing the stock market as a utility cost. Huang and Liu (2007) apply the concept of rational inattention to study the optimal portfolio decision of an investor who can obtain costly noisy signals about a state variable governing the expected growth rate of stock prices. Abel, Eberly, and Panageas (2007) study optimal inattention to the stock market in the context of Merton's (1971) model and the presence of information and transaction costs. Though modeling the dynamic nature of the problem we study is beyond the scope of this paper, these papers suggest that inattention might play an important role in such an analysis.⁸ Anecdotally many investors do seem to make portfolio decisions infrequently.⁹ Moreover, our empirical results are consistent with the clumping of tax-motivated trades occurring and generating price impact.

Finally, our work also relates to a growing empirical literature documenting price pressure in asset markets, a phenomenon initially suggested by Scholes (1972). Mitchell, Pulvino, and Stafford (2004) document price pressure subsequent to merger announcements and show that the trades of hedge funds appear to move prices away from fun-

⁷Stokey (2009) presents an extensive analysis of the issues related to inaction and infrequent adjustment that occur in stochastic control models with fixed costs.

⁸Intuitively, one is adding additional costs (the cost of observing and processing information, i.e. paying attention) and benefits (avoiding the clumping of trades near the turn of the tax year) to the dynamic problem studied in Constantinides (1984). It seems plausible that reasonable calibrations of the more complicated version of Constantinides exist where investors are reluctant to incur both transaction and attention costs until the end of the tax year draws near.

⁹Both Ameriks and Zeldes (2004) and Mitchell, Mottola, Utkus and Yamaguchi (2006) provide striking evidence that investors' portfolio adjustments are far from frequent.

damentals. Coval and Stafford (2007) document that extreme mutual fund flows result in forced trading that temporarily moves prices away from fundamental values.¹⁰ These price pressure findings are not restricted to equity markets; Ellul, Jotikasthira, and Lundblad (2010) and Mitchell, Pedersen, and Pulvino (2007) document price pressure in the bond and convertible bond markets respectively. In fact, the 2010 American Finance Association presidential address of Darrell Duffie (Duffie (2010)) uses the aforementioned assumption of investor inattention to model exactly these types of price pressure effects.

This paper is organized as follows. Section 1 briefly summarizes the most relevant recent literature and shows why both tax and interest rates should explain seasonal patterns in returns. Section 2 describes the data and the construction of our main variables. Section 3 analyzes the empirical implications for the cross-section and time-series of U.S. and U.K. stock returns, U.S. trading volume, and actual individual investor trading behavior, as well as the implications for performance attribution. Section 4 provides the conclusions.

1 The setting

A large previous literature has examined the turn-of-the-year effect in stock returns resulting from tax-motivated selling.¹¹ Recent empirical work by Klein (2001a, 2001b),

¹⁰Recent papers have explored some implications of the results of Coval and Stafford (2007). Lou (2009) shows that flow-driven demand shocks more generally affect prices than just in the extreme fire-sale situations of Coval and Stafford. Anton and Polk (2010) show that stocks that are relatively more connected by common institutional ownership covary more together, generating a cross-reversal effect.

¹¹The tax-selling hypothesis has been directly considered as an explanation for stock return seasonality by Wachtel (1942), Rozeff and Kinney (1976), Branch (1977), Dyl (1977), Roll (1983), Reinganum (1983), Chan (1986), Schultz (1985), Jones, Pearce and Wilson (1987), Reinganum and Shapiro (1987), Sims (1995), Reese (1998), Poterba and Weisbenner (2001), Grinblatt and Moskowitz (2004), and Ivković, Poterba and Weisbenner (2004).

Dammon, Dunn and Spatt (1989) study the valuation of tax options when short and long term capital gains tax rates differ. Bossaerts and Dammon (1994) study the option value to time the realization of capital gains and losses and Dammon and Spatt (1996) consider transaction costs and long and short term capital gains tax rates. Dammon, Spatt and Zhang (2001) build a dynamic consumption and portfolio decision model in the presence of capital gains taxes and short-sale restrictions. Dammon, Spatt and Zhang (2004) examine optimal asset allocation and location between taxable and tax-deferred accounts.

Grinblatt and Han (2005), Frazzini (2006), and Jin (2006) has more carefully examined this effect by studying the direct empirical links between a proxy for a stock's tax basis and patterns in returns. All of these papers relate measures of capital gains or losses to subsequent stock returns. Like these papers, our work exploits cross-sectional variation in a proxy for capital gains overhang; however, we also model and test a specific prediction about the magnitude of the effect for a given level of overhang.

A few researchers have also exploited time-series variation when testing the general predictions of a tax-based explanation for the turn-of-the-year effect. Most prominently, Poterba and Weisbenner (2001) study the way variation in the turn-of-the-year effect can be linked to changes in capital gains tax rates/regimes. Grinblatt and Moskowitz (2004) investigate the extent to which tax-loss selling drives the profits on technical trading strategies based on past return patterns. They find that trading profits are only statistically significant during high tax regimes.¹² The key contributions of our paper are to argue that interesting variation should also come from the interest rate channel and to provide empirical evidence that this channel is important.

Thus, the objective of this section is to build a measure that relates the maximum price distortion in December (or the turn-of-the-year effect) to all the relevant factors in a simple setting: the marginal seller's personal tax rate, the personal interest rate, and the capital gain/loss. We take the point of view of a marginal tax-motivated seller at the end of December.¹³ The seller is a rational investor, implying that his expectations of the price in January are unbiased. This investor evaluates the benefit of selling his holdings at the end of December (time t) at a distorted price in order to receive the tax benefit associated with realizing capital losses one year earlier (the current tax year instead of the following one).

For the sake of simplicity, assume the investor can sell stock i in January (time $t + 1$) at the true value of $P_{i,t+1}$ with no uncertainty. Under the assumption of downward sloping demand curves, tax-motivated selling will result in price pressure in December. Consequently, the investor must determine the lowest price at which he would be willing to sell the stock in December. To be clear, the investor solves for the

¹²A recent paper by Sialm (2007) studies dividend taxes and stock returns more generally to show that before-tax returns are higher for those stocks that have higher effective tax rates.

¹³The arguments in this section are made for a loser stock; however, a similar rationale applies to winner stocks as well.

December price $P_{i,t}$ that makes him indifferent between selling in either December or January and takes all other inputs as given. The reference price, RP_i , the price originally paid for the stock, determines the investor's cost basis for the purpose of taxation. The two other important parameters of this tax-loss harvesting decision are the capital gains tax rate, τ_t , and the one-year discount factor, $B_t = \frac{1}{1+r_t}$, that accounts for the time-value of money as well as the creditworthiness of the investor through an interest rate, r_t .¹⁴ This discount factor takes into account the present value cost of the tax consequences of selling in January rather than December.

We emphasize that a one-year discount factor is appropriate despite the fact that there is only a one-day difference between trading days in our framework.¹⁵ The reason for using a one-year discount factor is that delaying the sale by one day has the impact of delaying the tax benefit by one year. Therefore in our framework, the magnitude of the January rebound in stock returns depends on the one-year time value of the tax benefit. Note that for simplicity, we do not have a subscript i on τ or r since we are assuming the same tax and interest rate for all stocks at time t .

We equate the after tax proceeds of the sale in December and January:

$$\begin{aligned} [\text{Proceeds in December}] &= [\text{Proceeds in January}] \\ P_{i,t} - \tau_t(P_{i,t} - RP_i) &= P_{i,t+1} - \tau_t(P_{i,t+1} - RP_i)B_t. \end{aligned} \quad (1)$$

This equation can be rearranged into

$$-\tau_t(P_{i,t} - RP_i)(1 - B_t) = (P_{i,t+1} - P_{i,t})(1 - B_t\tau_t). \quad (2)$$

The equation above highlights the condition that makes the marginal seller indifferent. The equation says that the present-value loss of delaying the tax-credit must be compensated by the after-tax January rebound. For the sake of concreteness, we return to the example given in the introduction. At the temporarily low price of

¹⁴There are several complications of the tax code that are not considered in our analysis. For example, there is a cap on the size of the capital loss deduction one can make against personal income in any one year. Also, typically short-term capital gains are taxed at a higher rate than long-term capital gains. Moreover, the ability to implement a short-the-box strategy has changed over the time period we study. Finally, there are of course portfolio aspects of the decision. We ignore these complications for the sake of simplicity.

¹⁵Note that we ignore the one-trading-day discount effect on the sale proceeds for the sake of simplicity.

\$2.04, the investor can generate tax savings this year equal to $-30\% * (\$2.04 - 100) = \29.39 by harvesting the capital loss now. At an interest rate of 5%, delaying the harvest of this tax loss by one day results in a present value loss of $\$29.39 * (1 - 1/1.05) = \1.40 , as the investor must wait one year to receive the tax credit. This dollar amount is the value of the left-hand side of equation (2). However, this delay allows the investor to capture the January price rebound of $(\$4 - \$2.04) = \$1.96$ which results in an after-tax gain of $\$1.96 * (1 - 30\% / \$1.05) = \$1.40$, as the tax on the realized capital gain is paid in one-year's time.

Dividing by P_t and rearranging gives the stock's January rebound in units of return as

$$\frac{P_{i,t+1} - P_{i,t}}{P_{i,t}} = -\tau_t \frac{(1 - B_t)}{(1 - B_t \tau_t)} \frac{P_{i,t} - RP_i}{P_{i,t}}.$$

This equation shows that the stock's January rebound (the return from December to January) is a function of the capital gains tax rate, the level of the interest rate, and the capital gains overhang of the stock, $g_{i,t} = \frac{P_{i,t} - RP_i}{P_{i,t}}$. We further define $\gamma_t \equiv \tau_t \left(\frac{1 - B_t}{1 - B_t \tau_t} \right)$ in order to write the stock's tax-selling rebound in January as

$$\text{January rebound} = -\gamma_t g_{i,t} \tag{3}$$

We dub γ_t the *tax-selling premium*. Under our assumptions, this equation applies for all stocks. The capital gains overhang, $g_{i,t}$, is different for every stock, driving the cross-sectional variation in the effect, but the tax-selling premium, γ_t , is the same for all stocks, driving the time-series variation in the effect. Our description has focused on the case where the marginal investor in the stock has a negative capital gains overhang, and thus a positive January rebound return. Nevertheless, a similar rationale applies to stocks where the marginal investor has a positive capital gains overhang. A tax-motivated investor sells a winner stock this year rather than next year only if $P_{i,t}$ is so (temporarily) high that it compensates the investor for the present value loss of paying taxes this year rather than next year.

Our subsequent analysis exploits cross-sectional variation in $g_{i,t}$ and time-series variation in γ_t to explain return patterns in December and January. In particular, we measure the extent to which temporary price pressure occurs in December and

dissipates in January.¹⁶ We emphasize that the interest rate channel that our novel formulation identifies generates significantly more variation in the predicted magnitude of the effect than the tax rate channel (in fact, more than twice as much). The predicted value of γ , based on realized values of the two rates in question, varies from 8 to 660 basis points over the sample. This variation is primarily due to interest rates. If one were to fix interest rates at their average level over the sample, only allowing tax rates to vary, the resulting variation in γ is much smaller (97 to 338 basis points), roughly one-third of the variation in γ seen in the sample we study.

2 Data

In this section, we provide a description of the key variables used for these empirical tests. We first explain the way we compute our two key explanatory variables, the capital gains overhang, g , and the tax-selling premium, γ , and then describe the various control variables we employ. As the sources for these variables are standard datasets (CRSP, Compustat, TAQ, and the data from a large discount brokerage studied in Odean (1998)), we leave a detailed description of the raw data to Section 1 of the online Appendix.

2.1 Tax-selling premium

In theory, γ should be a function of the marginal investor’s capital gains tax rate and interest rate. Our implementation computes the U.S. version of γ using the one-year Fama-Bliss interest rate and the maximum capital gains tax rate each year, available from the Internal Revenue Service website.¹⁷ The U.K. version of γ is computed using the Bank of England base rate and the maximum capital gains tax rate each year, available from the HM Revenue & Customs website.

¹⁶The mispricing we investigate in December is equal to the mispricing in January in terms of dollars. However, when measured in returns, the alpha in December is not exactly equal to the alpha in January because the base price on which the return occurs is different. Our empirical work takes this difference into account. However, our description of the intuition ignores this difference for simplicity.

¹⁷By using the rates that were applied for each year t in question, we ignore the possibility that investors may anticipate that capital gains tax rates may change.

Although the appropriate interest rate depends on the credit worthiness of the marginal investor, we find that different interest rates imply similar variation in the U.S. version of γ . In the analysis that follows, we use the one-year Fama-Bliss interest rate primarily because this proxy has a long time-series. Section 2 of the online Appendix documents that using other interest-rate proxies that include an explicit credit component, such as the rates on auto and personal loans, generates very similar variation in γ over most of the common sample period.

2.2 Capital gains overhang

In theory, the relevant capital gains overhang, $g_{i,t}$, is that of the marginal seller, but this value obviously cannot be identified. Therefore, we use the capital gains overhang variable proposed by Grinblatt and Han (2005). They define capital gains overhang as the percentage deviation of a proxy for the stock's current reference price, $RP_{i,t}$, from the current price, $P_{i,t}$, where the proxy for a stock's current reference price is estimated using a turnover-weighted sum of end-of-week prices over the past 260 weeks, where $TO_{i,t}$ is the turnover of stock i in week t . Specifically, we measure $TO_{i,t}$ as the sum of daily trading volume relative to shares outstanding. Suppressing the subscript i for readability, the relevant equations are

$$\begin{aligned}
g_t &= \frac{P_t - RP_t}{P_t} \\
\text{with } RP_t &= \phi^{-1} \sum_{n=0}^{260} \hat{V}_{t,t-n} P_{t-n} \\
\text{where } \hat{V}_{t,t-n} &= TO_{t-n} \left[\prod_{\tau=1}^{n-1} (1 - TO_{t-n+\tau}) \right] \\
\text{and } \phi &= \sum_{n=0}^{260} \hat{V}_{t,t-n}
\end{aligned}$$

Therefore, the weights, $\hat{V}_{t,t-n} / \phi$, given to each past price, P_{t-n} , can be interpreted as the probability that the marginal seller bought the stock at that price, where $\hat{V}_{t,t-n}$ is a function of the past turnover from $t-n$ to $t-1$. Hence this probability is also equal to the probability that the reference price is equal to the price at $t-n$. Averaging over all possible reference prices yields the estimated cost basis.

The capital gains overhang measure has the following intuitive interpretation. If a stock had relatively high turnover exactly one year ago, but volume has been very low ever since, then the current shareholders are more likely to have bought the stock a year ago. Consequently, the price one year ago is a good proxy for the marginal investor’s purchase price. Conversely, if that stock instead had relatively high turnover in the most recent month, then last month’s price is a good proxy for the marginal investor’s purchase price. Note that we compute g for each firm using price and volume data from the CRSP database for U.S. firms and the Compustat Global database for U.K. firms.

2.3 Control Variables

We conduct cross-sectional regressions using both returns and selling pressure as dependent variables. The returns-based regressions consist primarily of daily firm-level returns, which are obtained from the CRSP database for U.S. firms and from Compustat Global for U.K. firms. The selling-pressure regressions, used for analyzing investor behavior, are also conducted at the daily frequency. We compute selling pressure, $Sell$, defined as the ratio of sell trades to all trades, following Lee and Ready (1991) and Hvidkjaer (2005) using the TAQ database. We further compute versions of selling pressure for small ($Sell_S$) and large ($Sell_L$) trades. Following Lee and Ready (1991), we set the cutoff point separating a large trade from a small trade at \$10,000.

The key variables in our regression are a firm’s capital gains overhang and the tax-selling premium. However, in most of the specifications, we also include other standard control variables. We include the book-to-market equity ratio (BM) in the regressions in order to capture the well-known value effect in the cross-section of average stock returns (Fama and French (1992)). We control for size (ME) given the evidence in Fama and French (1992) that size plays some role in describing the cross-section of average returns. We control for past returns over the last three years and trading volume as in Grinblatt and Han (2005), since our capital gains variable uses both as inputs. In particular, we decompose returns over the last three years into the one-month return, $r_{-1:0}$; the one-year return (excluding the past one-month return), $r_{-12:-1}$; and the three-year return (excluding the past one-year return), $r_{-36:-12}$. We calculate two measures of volume. The first is the average monthly turnover, \bar{V} , from the past 12 months. The second is monthly turnover, $TURN$, which is simply

the sum of daily turnover for the month in question. For both volume measures, note that we divide Nasdaq volume by two in an attempt to minimize the double counting of trades on that exchange.

2.4 Descriptive statistics of overhang portfolios

Though our analysis uses firm-level regressions, we first look at the characteristics of portfolios sorted on g to summarize how g varies in the cross-section and is related to other variables used in the finance literature to forecast cross-sectional variation in stock returns.

Table I reports equal-weight average characteristics for portfolios formed monthly on capital gains overhang. We choose equal-weight to correspond to our firm-level regressions which weight stocks equally. By definition, past returns are correlated with stocks' capital gains overhang.¹⁸ Nevertheless, it is interesting to see the extent to which there is spread in past returns over different horizons because of the capital gains overhang sort and the way that translates into characteristics that are indirectly driven by past returns, *SIZE* and *BM*. We find that high overhang stocks are typically large value momentum stocks while low overhang stocks are typically small growth losers. This tendency does not have to be true for every single stock (in fact, our stock-level regressions hope to separate these two sources of independent variation), but it is the case at the level of quintile portfolios. Note that seasonal effects have been documented in the average returns associated with many of these variables. By suggesting that previous analyses merely identified a tax-selling seasonal that varies through time, our framework provides an alternative explanation.

Also of particular interest is the fact that though there is no pattern in average monthly turnover over the past year, there is a pattern in the most recent monthly volume. Stocks with a low g experience relatively high turnover in December, while

¹⁸One possible concern is that variation in overhang is simply variation in momentum. In their Table I Panel B, Grinblatt and Han (2005) study the cross-sectional determinants of the capital gains overhang and show that about 59% of the cross-sectional variation in the capital gains variable can be explained by differences in past returns (over the past month, past year, and past three years), past turnover (over the past month, past year, and past three years), and firm size. Given that more than 40% of the variation remains unexplained and that all seven variables are each very significant, it is not just returns over the past year that are driving cross-sectional variation in overhang. Indeed, the thesis of Grinblatt and Han (2005) is that overhang clearly and reliably drives out $r_{-12:-1}$ in cross-sectional regressions forecasting returns.

stocks with a high g experience relatively high turnover in January. Even stronger patterns can be seen in our selling pressure variable $Sell$. Stocks with a low cost basis relative to price are being sold by both small ($Sell_S$) and large ($Sell_L$) investors in December. These patterns are consistent with optimal tax-selling behavior in the context we consider here.

3 Empirical Results

Our empirical analysis consists of three parts. First, we consider the ability of the product of g and γ to forecast cross-sectional and time-series variation in stock returns. Second, we examine the implications for trading volume and the trading behavior of individual investors. Finally, we analyze the consequences for aggregate returns and performance attribution.

3.1 Cross-sectional and time-series variation in firm-level returns

In this subsection, we focus on the analysis of the cross-sectional and time-series variation in firm-level returns. In particular, we show that the product of the tax-selling premium (γ , a function of capital gains rates and interest rates) and a stock's capital gains overhang (g) forecasts firm-level returns around the turn of the tax year. We first examine U.S. data and then turn to the U.K., where the tax and calendar year end do not coincide. In these regressions, we first cross-sectionally demean all firm-level data.

3.1.1 U.S. return regressions

Since our hypothesis has both cross-sectional and time-series implications, in Table II we estimate pooled regressions examining whether the interaction between γ and g forecasts either weekly or daily returns. Panels A and B of Table II report the main result; the remaining Panel estimates our benchmark specification over different subsamples for robustness.

We first estimate a regression forecasting weekly returns using the product of γ and g , as well as interacting that variable with nine dummy variables, eight for the four December and four January weeks and one for the rest of the year, February through November,

$$\begin{aligned} r_{i,t} = & a_1\gamma_{t-1}g_{i,t-1}FN \\ & + a_2\gamma_{t-1}g_{i,t-1}D1 + a_3\gamma_{t-1}g_{i,t-1}D2 + a_4\gamma_{t-1}g_{i,t-1}D3 + a_5\gamma_{t-1}g_{i,t-1}D4 \\ & + a_6\gamma_{t-1}g_{i,t-1}J1 + a_7\gamma_{t-1}g_{i,t-1}J2 + a_8\gamma_{t-1}g_{i,t-1}J3 + a_9\gamma_{t-1}g_{i,t-1}J4 + \varepsilon_{i,t} \end{aligned} \quad (4)$$

Standard errors are robust to cross-sectional correlation using the method of Rogers (1983, 1993).¹⁹ The first regression in Panel A shows that the effect of $\gamma * g$ is statistically significant in December and January using weekly dummies. The results are consistent with December momentum in stock returns which is explained by $\gamma * g$ and a subsequent reversal around the turn-of-the-year. Interestingly, the reversal seems to start during the last week of December.

The remaining regressions in Panel A add standard controls to the specification in equation (4). These controls include ME , BM , and g . These variables control for the well-known size, value, and momentum patterns in the cross-section of returns. We use g to control for momentum given Grinblatt and Han's finding that g subsumes simple price momentum's ability to describe the cross-section of average returns; however, note that we do include controls for past returns in subsequent regressions. We also interact ME with a dummy variable for January. Finally, we split the interaction, $\gamma * g * FN$, into $\gamma * g * FebJun$ and $\gamma * g * JulNov$.

These controls have little impact on our findings as the turn-of-the-year effect remains strong. However, the last week rebound becomes smaller and statistically insignificant. In all cases, we find that most of the January reversal occurs in the first week of January. We find that the ability of $\gamma * g$ to predict returns in February through November occurs entirely in the second-half of the year. This result is consistent with the potential clumping of tax-loss harvesting investors trades being partially anticipated by the market.

Panel B estimates a daily version of the fourth regression in Panel A in order to

¹⁹See Petersen (2009) for a careful study of the appropriateness of Rogers' (1983, 1993) estimator in various contexts.

shed more light on the effect seen during the last week of December. We continue to use weekly dummy variables to facilitate comparison with the weekly return regressions of Panel A, but we also add dummies for the business day before December 25th (XE dummy) and the business day before New Year’s Day (NYE dummy). After including these XE and NYE dummies, the last week of December exhibits a positive slope on the interaction $\gamma * g$. This result is consistent with tax-loss harvesting by taxable investors throughout the last week of the year, but with savvy investors purchasing temporarily depressed stocks on the last working days of the year.

Overall, Panels A and B suggest that tax-motivated selling, captured by the interaction of $\gamma * g$, can explain the cross-section of firm level returns during the turn of the year. We test for the joint significance of December weekly coefficients for both Panels A and B, finding that December coefficients are always jointly significant at the 1% level, with the exception of the second regression in Panel A, where the December coefficients are significant at the 5% level. January coefficients are jointly statistically significant at the 1% level for all regressions in Panels A and B.²⁰

We consider regression (1) in Table II Panel B to be our benchmark specification. The remaining regressions in Table II use this specification to test alternative hypotheses as well as document the robustness of our findings to different subsamples.

One alternative hypothesis is that γ is simply capturing a downward trend in the capital gains overhang effect, instead of the joint effect of interest rates and capital gains tax rates as specified in the formulation we derived. As a consequence, regression (2) in Table II Panel B interacts a linear time trend (*trend*) with g . We find a negative and statistically significant coefficient on *trend** g , which is consistent with a decreasing effect of g . However, this interaction does not subsume the $\gamma * g$ effect in December and January as coefficients remain roughly the same in magnitude and statistical significance. Regression (3) in Panel B considers the possibility that the interaction between g and the linear time trend differs as a function of the week of the year. This more flexible trend specification still does not subsume the $\gamma * g$ effect as coefficients and t-statistics associated with $\gamma * g$ remain strong in the weeks around the turn of the year.

Another alternative hypothesis is that it is really only one component of γ (either

²⁰The test for $(J1 + J2 + J3 + J4) + (D1 + D2 + D3 + D4) = 0$ yields an F-statistic of 3.85 with a p-value of 0.0499. Thus, we just reject the hypothesis that the sum of December and January coefficients are equal.

the interest rate or the capital gains tax rate) that is providing the forecasting power. Hence, we test whether interest rates (r) or tax rates (τ) are individually important in explaining the time-series variation in the capital gains overhang effect. Regression (4) in Table II Panel B shows that neither τ nor r in isolation interacts with g in a consistent fashion, providing additional support for our claim that γ is the correct conditioning variable.

In order to test the robustness of our results, we also estimate a regression with the same specification as in Grinblatt and Han (2005) in regression (5) of Panel B. In this regression we measure the seasonal pattern in our suggested variable, $\gamma * g$, while controlling for patterns in average returns related to the one-month return, $r_{-1:0}$, the one-year return $r_{-12:-1}$, the three-year return $r_{-36:-12}$, the average monthly turnover \bar{V} over the past 12 months, and $SIZE$.²¹

$$\begin{aligned}
r_{i,t} = & a_1\gamma_{t-1}g_{i,t-1}FN \\
& + a_2\gamma_{t-1}g_{i,t-1}D1 + a_3\gamma_{t-1}g_{i,t-1}D2 + a_4\gamma_{t-1}g_{i,t-1}D3 + a_5\gamma_{t-1}g_{i,t-1}D4 \\
& + a_6\gamma_{t-1}g_{i,t-1}J1 + a_7\gamma_{t-1}g_{i,t-1}J2 + a_8\gamma_{t-1}g_{i,t-1}J3 + a_9\gamma_{t-1}g_{i,t-1}J4 \\
& + a_{10}g_{i,t-1} + a_{11}r_{i,-1:0} + a_{12}r_{i,-12:-1} + a_{13}r_{i,-36:-12} \\
& + a_{14}\bar{V}_{i,t-1} + a_{15}\ln ME_{i,t-1} + \varepsilon_{i,t}
\end{aligned}$$

Again we find that the product of γ and g predicts returns in a manner consistent with our hypothesis.²²

In Panel C of Table II, we re-estimate our benchmark regression over different sub-periods. Consistent with our hypothesis, $\gamma * g$ has the expected effect around the turn-of-the-year in all sub-periods.

²¹Grinblatt and Han (2005) use a slightly different measure of size than Fama and French (1992). For consistency's sake, we use the appropriate definition in the corresponding specification. However, we ignore the minor difference between these two definitions of size when describing the results.

²²We have re-estimated these equations using different tax rates, including both the average maximum tax rate and the average federal marginal tax rate from the NBER's TAXSIM dataset [see Feenberg and Coutts (1993)]. Our conclusions remain qualitatively the same. We report results using the maximum capital gains tax rate as that tax rate is available over the longest time period.

3.1.2 U.K. return regressions

The fact that the turn-of-the-tax-year coincides with the turn-of-the-calendar-year in the U.S. has resulted in a long debate as to whether tax-motivated trading or window dressing is causing the turn-of-the-year effect. Researchers have argued that window dressing could explain similar return patterns as fund managers sell losers and buy winners at the end of the reporting period to make their year-end portfolios look strong. Our approach helps distinguish between these two hypotheses as there does not seem to be any obvious reason that the magnitude of the window dressing effect would be related to time-series variation in γ .²³ Nevertheless, we take this concern seriously and turn to international data for further insight.

We test the same hypothesis with international data, choosing the U.K. because its tax year does not coincide with the calendar year. Specifically, the tax year in the U.K. begins on the 6th of April and ends on the 5th of April of the next calendar year. As a result, the U.K. provides a clean setup to test these two plausible hypotheses. Any seasonality in the U.K. stock market around the turn-of-the-tax-year would be strong evidence for tax-motivated trading causing seasonality in stock returns.

We are not the first to use U.K. data to test the tax-selling hypothesis. In particular, Reinganum and Shapiro (1987) show that after the introduction of capital gains taxes in the U.K., the difference in April returns between winners and losers becomes significantly greater than zero, consistent with a tax-loss selling story. Our primary empirical contribution is to show that this premium varies with the interest rate as predicted by our formulation.²⁴

The results using U.K. data provide further evidence of tax-motivated trading, as Table III shows results similar to Table II. Seasonality in U.K. returns indeed occurs at the turn-of-the-tax-year and varies as a function of our tax-selling premium. All coefficients are positive in March and negative in April. Coefficients are jointly statistically significant at the 1% level in both March and April.

²³Other researchers have examined tax-motivated price pressure stories that occur at times other than the turn of the year to rule out alternative explanations such as window dressing. See, for example, Guenther and Willenborg (1999), Blouin, Raedy and Shackelford (2003), and Dai, Maydew, Shackelford and Zhang (forthcoming).

²⁴Other differences include the fact that Reinganum and Shapiro (1987) examine only monthly stock returns and use an arguably cruder proxy for a stock's capital gains overhang. In contrast, we use daily returns and measure capital gains overhang as in Grinblatt and Han (2005).

3.2 Cross-sectional and time-series variation in trading behavior

The time-series and cross-sectional patterns we have found in firm-level returns are consistent with tax-motivated selling pressure. In this section, we examine further implications of that explanation, particularly the way our suggested variables explain seller-initiated volume and the behavior of individual investors. First, we examine all trading volume at the turn of the year. Unlike previous research, we exploit a long panel of trading data, namely the TAQ database, and categorize all trades over the 1993-2005 period as small or large, buy or sell.²⁵ Second, we also examine trading patterns by studying the actual trades of individual investors, obtained from Odean's dataset, to confirm that these investors harvest (defer) capital losses (gains) based on the level of our tax-selling premium.

3.2.1 Seller-initiated trading volume

We build on the results of the previous subsection to test our framework's ability to explain time-series and cross-sectional variation in seller-initiated trades as a whole as well as in small and large trade subsets. We examine these subsets as previous research has argued that small trades are primarily from individuals while large trades are primarily from institutions. We would expect negative overhang stocks to have high selling pressure in December followed by low selling pressure in January. Similarly, we expect the opposite effect in the case of positive overhang stocks.

In Table IV, we forecast the level of selling pressure ($Sell$, $Sell_S$, $Sell_L$) in Panel A and the first difference of those variables in Panel B. Throughout the Table, we use the same independent variables as Table II Panel B regression (5). Specifically, we estimate

²⁵In contrast, Sias and Starks (1997) use TAQ data from only December 1990 and January 1991 to examine a similar question.

$$\begin{aligned}
Sell_{i,t} = & a_1\gamma_{t-1}g_{i,t-1}FN \\
& +a_2\gamma_{t-1}g_{i,t-1}D1 + a_3\gamma_{t-1}g_{i,t-1}D2 + a_4\gamma_{t-1}g_{i,t-1}D3 + a_5\gamma_{t-1}g_{i,t-1}D4 \\
& +a_6\gamma_{t-1}g_{i,t-1}J1 + a_7\gamma_{t-1}g_{i,t-1}J2 + a_8\gamma_{t-1}g_{i,t-1}J3 + a_9\gamma_{t-1}g_{i,t-1}J4 \\
& +a_{10}g_{i,t-1} + a_{11}r_{i,-1:0} + a_{12}r_{i,-12:-1} + a_{13}r_{i,-36:-12} \\
& +a_{14}\bar{V}_{i,t-1} + a_{15}\ln ME_{i,t-1} + \varepsilon_{i,t}
\end{aligned} \tag{5}$$

in Panel A and

$$\begin{aligned}
Sell_{i,t} - Sell_{i,t-1} = & a_1\gamma_{t-1}g_{i,t-1}FN \\
& +a_2\gamma_{t-1}g_{i,t-1}D1 + a_3\gamma_{t-1}g_{i,t-1}D2 + a_4\gamma_{t-1}g_{i,t-1}D3 + a_5\gamma_{t-1}g_{i,t-1}D4 \\
& +a_6\gamma_{t-1}g_{i,t-1}J1 + a_7\gamma_{t-1}g_{i,t-1}J2 + a_8\gamma_{t-1}g_{i,t-1}J3 + a_9\gamma_{t-1}g_{i,t-1}J4 \\
& +a_{10}g_{i,t-1} + a_{11}r_{i,-1:0} + a_{12}r_{i,-12:-1} + a_{13}r_{i,-36:-12} \\
& +a_{14}\bar{V}_{i,t-1} + a_{15}\ln ME_{i,t-1} + \varepsilon_{i,t}
\end{aligned} \tag{6}$$

in Panel B. Note that we expect both $Sell_{i,t}$ and $Sell_{i,t} - Sell_{i,t-1}$ to move in the opposite direction of the predicted return; and, therefore, we now expect a positive (negative) slope in January (December) on our tax-selling variable. As in the return regressions, all firm-level variables are cross-sectionally demeaned. Standard errors are robust to simultaneous correlation both across firms and across years based on the method developed by Thompson (forthcoming).

We do find that both returns and selling pressure exhibit similar seasonality, as selling pressure results are consistent with the return regressions shown in Table II. Panel A in Table IV reports the results from regressions forecasting the level of selling pressure. We find that December slopes on $\gamma * g$ are all negative and highly statistically significant, indicating taxable investors are selling negative overhang stocks and holding on to positive overhang stocks in December. As expected, January exhibits the opposite pattern.

For example, in the last week of December, the coefficient on $\gamma * g$ is -1.893 with a t -statistic in excess of 11. Then, in the case of a negative overhang stock, selling pressure reverses into buying pressure after the turn of the year as slopes on $\gamma * g$

turn positive in January. Specifically, we find a reversal in selling pressure in the first week of January with a statistically-significant coefficient of 1.718. These results are economically quite large, at least when compared to the coefficient on $\gamma * g$ of -0.001 throughout February and November. We also find that the coefficients associated with the business days before Christmas and New Year's Day are consistent with the corresponding coefficient estimates of the return regressions.

The analysis in Section 1 indicates that we should expect $\gamma * g$ to forecast the level of selling pressure. Nevertheless, we find that results remain statistically significant even when we forecast changes in selling pressure. In this case, we are analyzing whether the change in selling pressure of low/negative capital gains overhang stocks increases as we approach the end of the year. Panel B shows that this increase indeed occurs, as coefficients in December are all negative. The selling pressure of low overhang stocks increases over the course of December (negative coefficients), but suddenly declines in the first week of January (positive coefficient). Note that the slope on the NYE dummy interaction is positive and highly statistically significant, implying a large change in selling pressure just before the turn of the year.

In both panels we also split the data into small and large trades. We do this as past research (Lee and Ready (1991) and others) has associated small trades with buying by individual investors and large trades with buying by institutional investors. We find the reversal in selling pressure to be strong and more statistically significant in the case of small trades, but present for both subsets. Though the results for small and large trades are very similar, the January slopes in Panel A seem to be slightly higher for small trades. Interestingly, the savvy buying pressure in the last week of the year seems to come from institutional investors on Christmas Eve and from individual investors on New Year's Eve.

Past research has looked for similar links between returns and selling pressure. Ritter (1988) finds that individual investors who are customers at Merrill Lynch place more sell orders in December than in January. While this finding is consistent with tax selling, a limitation is that it focuses only on a small subgroup of investors. Sias and Starks (1997) show that individuals sell stocks at the end of the year. This evidence is consistent with tax-motivated selling, but they find the individuals also sell past one-year winners in December. They view this result as inconsistent with tax selling, but to the extent that return momentum is a poor proxy for capital gains overhang, it may be difficult to draw conclusions about tax-motivated selling from their results. Another limitation of Sias and Starks (1997) is that they use TAQ data

from only December 1990 and January 1991.

3.2.2 Actual individual trades

We examine trading patterns by studying the actual trades of individual investors to confirm that these investors harvest (defer) capital losses (gains) based on the level of our tax-selling variables. In particular, Figure 1 reports the results of what is essentially a difference-in-difference test of the trading implications of equation (1). That figure shows the *difference* in the propensity to realize capital gains/losses in December compared to January, for *different* levels of γ . In particular, we split the sample into above-median and below-median γ .

We process all of the trades in the Odean dataset in the following way. We follow each stock in the database from the time it was purchased until the time it was eventually sold. We keep track of the close for that stock at the end of each day in between the purchase date and the eventual sell date, using every closing price to calculate an unrealized capital gain/loss. For each of eleven evenly-spaced bins ranging from -100% to >100%, these unrealized gains and losses are then compared to observed realized gains and losses to measure a tendency for investors to sell as a function of capital gain/loss. Then for each bin, we subtract the January propensity to sell from the December propensity to sell. These turn-of-the-year differences to sell are plotted separately for high γ years and low γ years. The average value of γ for the high γ years subset is 0.040, while the average value of γ for the low γ years subset is 0.022.

There are two strong conclusions to draw from the figure. First, investors tend to accelerate the realization of capital losses in December (compared to January). Second, this tendency is much higher in those years when γ is higher. Together these two facts confirm the central prediction of our conjecture: investors' propensity to sell at the turn of the year depends on the product of the capital gains overhang, g , and the tax-selling premium, γ , which is a function of the interest and tax rate environment. Our framework also suggests that investors may delay realizing capital gains in high γ years. However, because of the non-linear relation between capital gains and capital gain overhang, a relatively large capital gain results in a relatively small amount of overhang. Consequently, one would not expect variation in γ to generate much variation in selling probabilities for stocks with unrealized capital gains, and it does not.

3.3 Implications for performance attribution

Our analysis has tried to measure the firm-specific and aggregate variables that drive cross-sectional and time-series patterns in average returns at the turn of the year. To do so, we have used a particular measure of firm-specific capital gains overhang and have controlled for other well-known patterns in the cross-section such as a stock's size, its book-to-market equity ratio, and its return momentum that are known to be correlated with our particular measure of a firm's capital gains overhang.

However, given this correlation, a natural complementary question to ask is the following: To what extent can the tax-selling effect drive market beta and the abnormal return associated with bets on the size, book-to-market, and momentum characteristics? To answer these questions, we first document the extent to which the market return can be forecast by our tax-selling variables. We then estimate conditional CAPM time-series regressions pricing the three Fama-French/Carhart non-market factors.

First, we test whether tax-motivated selling can explain aggregate returns in January. To do so, we measure g_M , the value-weighted average of firm-level measures of g . Table V shows that $\gamma * g_M$ does predict market returns in January in all of the specifications we consider. This effect is both statistically and economically significant. Specifically, based on the specification of Table V regression 1, a one standard deviation increase in the joint product of $\gamma * g_M$ results in a decrease in the equity premium of approximately one percent. We also report the results of specifications that control for the independent effect of γ or g_M . Note that we find a statistically significant relationship despite the inclusion of the aggregate book-to-market variable in these regressions.

As we find that market returns are indeed affected by tax-selling behavior, we estimate conditional CAPM time-series regressions that include $\gamma * g$ as a conditioning variable. In these regressions, we analyze the three Fama-French/Carhart non-market factors. We choose these three factors because of their widespread use in academic research. In particular, these factors represent more reasonable implementations of strategies based on size, book-to-market, or momentum characteristics than the strategies implicit in our earlier cross-sectional regression tests. For comparability, we create a zero-cost overhang factor that is formed in a similar way to the momentum factor of Carhart. Specifically, each month we sort all NYSE stocks on our overhang measure and calculate 20th and 80th percentile breakpoints. We then

buy all NYSE-AMEX-NASDAQ stocks that are below the NYSE 20th percentile and sell all NYSE-AMEX-NASDAQ stocks that are above the NYSE 80th percentile. The positions in the long and short sides are value-weight. Thus, we will be able to show both the extent to which a tax-selling premium is a component of the premiums on these well-known factors as well as the nature of the tax-selling premium on value-weight positions based on a traditional sorting approach.

Figure 2 plots the January return on the TAX factor for each of the years of the sample against an OLS forecast of the expected January return on the TAX factor using the product of the tax-selling premium and the factor’s capital gains overhang, $\gamma * g_{TAX}$. As detailed in the Figure legend, the regression coefficient in that regression is -1.99 with an associated t-statistic of -3.52. That regression’s adjusted R^2 is 17.7%. These statistics and this figure confirm that there is a time-series relation between the January return on TAX and our predicted January rebound return as well as documents that the average January return on TAX is positive.²⁶ Moreover, these results confirm that the general conclusion from the firm-level regression analysis is robust to weighting firms by market capitalization.

The specification of our conditional CAPM regression follows from two of our results. Specifically, we have shown that 1) there is time-series and seasonal variation around the turn of the year in the cross-sectional premium for the capital gains overhang variable and 2) this variation can be observed at the market level as well. The first finding indicates that our conditional CAPM regression should have the intercept be a function of the trading strategy’s forecasted December dislocation and January rebound. That premium, of course, will depend on the trading strategy’s beginning-of-period capital gains overhang, the tax-selling premium which depends on the beginning-of-period tax and interest rates, and the particular month in question, as we derived in Section 1. Not only do we allow the alpha in our CAPM regression to vary through time but we also consider time variation in the regression’s market beta. Cochrane (2001) points out that a time-varying CAPM beta only affects pricing to the extent that the beta is correlated with time-variation in the market premium. There-

²⁶One could arguably attribute the large positive realized return (35%) on the TAX factor in January 2001 to the large negative return to a momentum strategy (-24%) in January as the tech boom subsided. Regardless, the 2001 observation is not influential. In fact the t -statistic and R^2 increase to -4.72 and 29.08% respectively when that observation is dropped from the sample.

Note that the relation in Figure 2 continues to be statistically significant if one instead predicts CAPM-adjusted returns instead of raw returns as in the Figure. If one imposes a regression coefficient of -1, the resulting intercept is statistically insignificant from zero under either benchmarking approach.

fore, the second finding (the market’s tax-selling premium forecasts the subsequent excess return on the market) indicates that our conditional CAPM regressions should have a time-varying beta that is a function of the market’s forecasted December dislocation and January rebound. As at the firm level, that predictable return will depend on the market’s beginning-of-period capital gains overhang, the tax-selling premium (which depends on the beginning-of-period tax and interest rates), and the particular month in question.

Table VI summarizes the extent to which cross-sectional and time-series variation in tax-selling premiums drive conditional alphas and betas for the three well-known factor portfolios HML, SMB, UMD and our low-minus-high overhang portfolio, which we denote as TAX. Note that we attribute performance of the returns on the actual factors generated by Ken French (obtained from his web site). However, we can only proxy for the capital gains overhang of French’s factors as not all of the stocks in the factor portfolios have the necessary data our measure requires. In particular, while our firm-level overhang measure requires five years of price and volume data, these strategies do not. Presumably, our findings would be have been strengthened if instead, we had priced the return on factors whose construction imposed a five-year data requirement as well.

The first regression of each panel in Table VI first documents the extent of seasonality in the CAPM alpha of the factors being considered. For TAX, HML, and SMB, a significant portion of their average abnormal return occurs in January. Figure For UMD, the strong average returns outside of the turn of the year are partially offset by a very large negative premium in January.

The second regression of each panel in Table VI then demonstrates that variation in the market’s tax-selling effect drives beta at the turn of the year. For the three factor portfolios TAX, HML, and SMB, when the market’s forecasted tax-selling January rebound, $-\gamma * g_M$, is relatively high, January betas are predictably relatively high as well.²⁷ In each of these cases, December betas are correspondingly relatively low, though only the SMB estimate is statistically significant. As one might expect from the evidence in Table I, we find the opposite effect for the momentum portfolio. The January beta for the momentum portfolio is predictably higher when the market’s tax-selling premium is relatively low. Since Table V shows that the market’s tax-

²⁷For the sake of interpretability, we normalize the time-series $\gamma * g_M$ so that the coefficients on *RMRF* represent the average beta during the months in question and the coefficient on $\gamma * g_M * \text{RMRF}$ represent the change in beta for a one standard deviation move in $\gamma * g_M$.

selling premium forecasts the excess return on the market, it is not surprising that controlling for this conditional beta effect reduces the absolute magnitude of the alpha of these four trading strategies in January.

Figure 3 uses higher-frequency estimates of the beta of the components of the TAX bet to confirm that the link between the market risk of the TAX bet and the market’s forecasted tax-selling January rebound return is particularly present in the days surrounding the turn of the year. Specifically, Figure 3 graphs five-day rolling betas throughout December and January for low, middle, and high overhang quintile portfolios.²⁸ When the market has a relatively high forecasted January rebound because of both a large capital loss in December and high tax and interest rates, low overhang stocks covary much more with the market in the days subsequent to the turn of the year than do high overhang stocks.

Similarly, Figure 3 confirms that the predictability in daily returns and selling pressure depends on the market’s expected January rebound return. Figure 3 shows that patterns in both daily returns and selling pressure are stronger when the tax-selling effect in the market return is stronger. Specifically, when the market’s expected January rebound return, $-\gamma * g_M$, is large, low overhang stocks display much higher selling pressure in December and more strongly outperform high overhang stocks in January.²⁹ Again these results are more concentrated on the days very close to the turn of the year.

The third regression of each panel in Table VI not only controls for time-varying

²⁸We compute betas for the capital gains overhang quintile portfolios as follows. Trading days are numbered (between -20 and +20) around the turn of each year such that 0 is the last trading day in December and +1 is the first trading day in January. Betas are then computed versus the CRSP value-weighted market portfolio for each trading day. Thus, the day(0) beta accounts for the covariance between quintile portfolio returns and market returns on the last trading day of each year. This procedure yields a series of 41 trading day betas for each quintile portfolio. We then use these series to compute trailing five-day moving averages for each quintile portfolio.

Note that Figure 3 plots the daily moving average betas conditional on the market’s tax-selling alpha. Thus, the procedure described above is slightly modified so that the trading day betas are computed separately for years with positive versus negative expected January market rebound return. Our split compares positive versus negative rather than simply high versus low values of the January rebound return to be consistent with the corresponding regression (3) of Table 6 Panel A.

²⁹The difference between the cumulative January return for the low overhang portfolio and the high overhang portfolio is 4.00% during years of a low expected January rebound return for the market and 8.72% during years of a high expected January rebound return for the market. Each of these differences is statistically significant at the 1% level. Moreover, the difference between these cumulative returns of 4.72% is significant at the 5% level (t -statistic of 2.09).

beta but also attributes a portion of the remaining conditional alpha to our strategy-specific tax selling premium variable. We find that though January alphas remain economically and statistically significant, they are reduced significantly in the case of SMB and UMD. The January alpha for SMB is reduced by 44%, while the January alpha for UMD is reduced by 37%. Interestingly, for two of the three factors, SMB and UMD, the non-tax alpha from February to November becomes statistically insignificant. However, the point estimate of the HML non-tax alpha from February to November actually increases, though by less than 13%.

In summary, Table VI shows that a portion of the risk and abnormal return of the Fama-French/Carhart non-market factors can be linked to our tax-selling premium, as the tax-selling effect is strong in both market and factor portfolios. These findings have important implications for those researchers examining economic stories describing time-variation in the properties of these factors.³⁰

4 Conclusions

Our framework implies that temporary distortion in stock prices may arise because of the taxation of capital gains. In particular, we exploit the tradeoff a rational investor faces when realizing tax losses (gains) this tax year instead of next tax year in the presence of temporary downward (upward) price pressure. Optimal tax selling can generate stock return overreaction at the end of the tax year and a corresponding reversal at the beginning of the subsequent tax year. The magnitude of these predictable returns is not only a function of a stock's tax basis but also a function of interest rates and capital gains tax rates, which together bound the temporary distortion. The vast amount of literature on tax-selling at the turn of the year ignores time-series variation in the effect. The two previous papers (Poterba and Weisbenner (2001) and Grinblatt and Moskowitz (2004)) that do examine time-series variation in the effect only look at variation resulting from the tax rate. The interest rate channel

³⁰For example, Chordia and Shivakumar (2004) argue that returns on momentum strategies can be explained once they are adjusted for the predictability of stock returns based on macroeconomic variables. These variables include the interest rate which is an important component of our tax-selling premium. Cooper, Gutierrez, and Hameed (2004) forecast returns on momentum strategies with the state of the market, which they define as whether the past three-year return on the market is positive or negative. That definition is clearly related to our measure of market overhang, g_M , that drives seasonal patterns in risk for the momentum factor.

that we identify generates significantly more variation in the predicted magnitude of the effect than the tax rate channel (in fact, more than twice as much).

A variety of empirical evidence confirms this prediction. We document patterns in the cross-section of average returns at the turn of the tax year that are consistent with our story. Our main tests use U.S. data, but additional tests using U.K. data provide an important out-of-sample confirmation, as the U.K. tax and calendar year end differ. We also identify trading patterns that are consistent with tax-motivated selling driving these temporary movements in stock prices. Stocks with low capital gains overhang have more selling pressure in individuals' trades at the turn of the tax year than stocks with high capital gains overhang, and this imbalance also varies with the same function of interest rates and capital gains tax rates. Moreover, in the actual trades of investors using a large discount brokerage, the tendency to harvest losses in December rather than in January also varies with this bound. Finally, we find that these effects are also present in aggregate returns. As a consequence, performance attribution at the turn of the year is not only affected by the firm-level tradeoff, but also by distortion in measuring risk arising from this tax-selling based common factor.

Interestingly, our emphasis on the importance of the interest rate also explains why recent returns to strategies exploiting that phenomenon have been low. These low returns are not due to savvy investors eliminating the effect, but instead are explained by the rather low interest rates in the recent data. As interest rates rise, our formulation predicts that the January effect should return.

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Table I: Descriptive Statistics

This table reports various characteristics of capital-gains-overhang-sorted quintile portfolios formed each month. These portfolios are equal-weight portfolios. We compute capital gains overhang, g , as in Grinblatt and Han (2005). The characteristics include a decomposition of returns over the last three years into the one-month return, $r_{-1:-0}$; the one-year return (excluding the past one-month return), $r_{-12:-1}$; and the three-year return (excluding the past one-year return), $r_{-36:-12}$. Market capitalization, ME , and the book-to-market equity ratio, BM , are computed as in Fama and French (1992). BM is the previous fiscal year's ending book value divided by the corresponding year's December market value. ME is the latest end-of-June market value in thousands. We also report the average monthly turnover, \bar{V} , from the past 12 months as well as the monthly turnover, $TURN$, the sum of daily turnover within the past month. For both volume measures, we divide Nasdaq volume by two in an attempt to make volume numbers comparable across exchanges. We compute $Sell$ as the fraction of seller-initiated trades relative to all trades for both small (S) and large (L) trades. The cut-off delimiting a small versus a large trade is \$10,000, as in Lee and Ready (1991). The sample starts in February of 1954 and ends in December 2008.

Panel A: December

	g	$r_{-1:0}$	$r_{-12:-1}$	$r_{-36:-12}$	ME	BM	\bar{V}	$TURN$	$Sell_S$	$Sell_L$
H	0.28	0.043	0.512	0.717	1856	0.66	0.043	0.047	0.51	0.52
4	0.09	0.023	0.251	0.494	2015	0.78	0.054	0.052	0.52	0.51
3	-0.07	0.011	0.124	0.391	1546	0.87	0.057	0.054	0.53	0.52
2	-0.33	0.000	0.000	0.294	887	0.97	0.055	0.055	0.56	0.54
L	-1.90	-0.021	-0.198	0.065	190	1.29	0.044	0.053	0.61	0.57

Panel B: January

	g	$r_{-1:0}$	$r_{-12:-1}$	$r_{-36:-12}$	ME	BM	\bar{V}	$TURN$	$Sell_S$	$Sell_L$
H	0.30	0.054	0.544	0.741	1719	0.68	0.039	0.052	0.51	0.52
4	0.11	0.042	0.264	0.505	1955	0.79	0.050	0.058	0.52	0.51
3	-0.03	0.040	0.133	0.402	1529	0.87	0.053	0.058	0.52	0.51
2	-0.27	0.048	0.016	0.318	936	0.97	0.054	0.057	0.52	0.51
L	-1.70	0.082	-0.170	0.085	195	1.27	0.043	0.043	0.54	0.54

Panel C: February-November

	g	$r_{-1:0}$	$r_{-12:-1}$	$r_{-36:-12}$	ME	BM	\bar{V}	$TURN$	$Sell_S$	$Sell_L$
H	0.29	0.040	0.527	0.681	1672	0.69	0.040	0.050	0.51	0.52
4	0.12	0.018	0.266	0.461	1972	0.80	0.051	0.055	0.51	0.51
3	-0.02	0.008	0.132	0.369	1660	0.87	0.054	0.055	0.52	0.51
2	-0.24	0.000	0.008	0.287	956	0.96	0.054	0.052	0.53	0.52
L	-1.48	-0.008	-0.189	0.065	198	1.23	0.044	0.040	0.55	0.55

Table II: Pooled Return Regression Estimates: 1954-2008

We report the results from pooled regressions of day or week t stock returns on $t - 1$ characteristics. Characteristics are measured on a weekly basis for conciseness. All firm-specific variables, defined in Table I, are cross-sectionally demeaned, and when appropriate, interacted with our proposed tax-selling premium variable, $\gamma_t = \tau_t \left(\frac{1-B_t}{1-B_t\tau_t} \right)$, a function of capital gains tax rates (τ_t) and interest rates ($r_t = \frac{1}{B_t} - 1$) as derived in Section 1 of the paper, and with dummy variables for different periods of the year. The dummy variables are FN , $D(W)$, and $J(W)$ for February-November, December, and January respectively and refer to the month of the return being predicted, with W indicating the week of the particular month in question. T -statistics (in parentheses) are robust to cross-correlation in the residuals using the clustered standard errors of Rogers (1983, 1993). We also consider a case where we split the dummy variable FN into two halves: $FebJun$ and $JulNov$. The sample starts in February of 1954 and ends in December 2008. Panel A presents weekly regressions of returns on weekly interactions of weekly dummies, g and γ , also including g , ME and BM as controls. Panel B reports daily return regressions using weekly variables for conciseness and direct comparison with Panel A. We expand the set of interactions to also include dummies for the business day before Christmas (XE) and the business day before New Year's Day (NYE). Regression (2) in Panel B accounts for a possible trend in the effect of g on returns. Regression (3) in Panel B considers the possibility that the trend depends on the month, week, or day of the year. Regression (4) in Panel B analyzes whether the interactive effect of γ can be explained simply through interactions with its components, capital gains tax rates (τ) or interest rates (r) individually. Regression (5) in Panel B considers an alternative set of controls using the same variables as in Grinblatt and Han (2005), also defined in Table I. Panel C shows sub-sample analysis of the first regression in Panel B. The regressions correspond to the sub-periods 1963-2008, 1954-2008, 1980-2008, and 1993-2008 respectively. For Panel A, these regressions generally take the form

$$\begin{aligned}
 r_{i,t} = & a_1 \gamma_{t-1} g_{i,t-1} FN \\
 & + a_2 \gamma_{t-1} g_{i,t-1} D1 + a_3 \gamma_{t-1} g_{i,t-1} D2 + a_4 \gamma_{t-1} g_{i,t-1} D3 + a_5 \gamma_{t-1} g_{i,t-1} D4 \\
 & + a_6 \gamma_{t-1} g_{i,t-1} J1 + a_7 \gamma_{t-1} g_{i,t-1} J2 + a_8 \gamma_{t-1} g_{i,t-1} J3 + a_9 \gamma_{t-1} g_{i,t-1} J4 \\
 & + a_4 g_{i,t-1} + a_5 \ln ME_{i,t-1} + a_6 \ln BM_{i,t-1} + \varepsilon_{i,t}.
 \end{aligned}$$

Panel A					
	(1)	(2)	(3)	(4)	(5)
$\gamma * g * FN$	-0.035 (-3.91)	-0.024 (-2.63)	0.056 (2.68)	0.054 (2.60)	
$\gamma * g * D1$	0.135 (1.71)	0.126 (1.57)	0.207 (2.50)	0.205 (2.49)	0.204 (2.48)
$\gamma * g * D2$	0.155 (3.08)	0.127 (2.02)	0.208 (3.21)	0.206 (3.19)	0.202 (3.06)
$\gamma * g * D3$	0.216 (4.51)	0.219 (4.04)	0.299 (4.97)	0.298 (4.96)	0.294 (4.90)
$\gamma * g * D4$	-0.134 (-2.27)	-0.159 (-2.50)	-0.079 (-1.20)	-0.081 (-1.22)	-0.076 (-1.15)
$\gamma * g * J1$	-1.000 (-5.08)	-1.009 (-5.38)	-0.927 (-5.02)	-0.913 (-4.98)	-0.914 (-4.99)
$\gamma * g * J2$	-0.391 (-3.05)	-0.383 (-2.79)	-0.301 (-2.27)	-0.286 (-2.17)	-0.286 (-2.19)
$\gamma * g * J3$	-0.271 (-2.73)	-0.244 (-3.07)	-0.162 (-2.00)	-0.146 (-1.85)	-0.149 (-1.87)
$\gamma * g * J4$	-0.312 (-4.81)	-0.300 (-4.17)	-0.219 (-2.89)	-0.203 (-2.70)	-0.199 (-2.66)
$\gamma * g * FebJun$					0.015 (0.62)
$\gamma * g * JulNov$					0.086 (4.13)
g			-0.002 (-4.01)	-0.002 (-4.01)	-0.002 (-4.00)
$\ln(ME)$		-0.020 (-3.11)	-0.012 (-1.87)	-0.009 (-1.34)	-0.011 (-1.65)
$\ln(BM)$		0.057 (3.13)	0.049 (2.68)	0.049 (2.68)	0.022 (1.60)
$\ln(ME) * J$				-0.044 (-8.95)	-0.045 (-8.94)

Panel B							
	(1)	(2)	(3)		(4)		(5)
			interact dummies with both		replace γ with both		
			$\gamma * g$	$g * trend$	τ	r	
$\gamma * g * FN$	0.007 (1.95)	-0.003 (-0.66)	-0.002 (-0.50)	-1.5E-05 (-2.86)	0.115 (4.58)	-0.004 (-1.81)	0.006 (1.72)
$\gamma * g * D1$	0.036 (2.24)	0.025 (1.58)	0.021 (1.19)	7.6E-06 (0.48)	0.059 (0.42)	-0.015 (-2.53)	0.040 (2.46)
$\gamma * g * D2$	0.028 (1.39)	0.017 (0.87)	0.021 (1.08)	-2.9E-05 (-2.25)	0.173 (0.93)	-0.008 (-2.95)	0.038 (2.43)
$\gamma * g * D3$	0.055 (4.64)	0.044 (3.49)	0.030 (3.14)	4.9E-05 (2.24)	0.105 (0.46)	-0.005 (-1.73)	0.057 (5.49)
$\gamma * g * D4$	0.044 (4.41)	0.033 (3.28)	0.033 (3.42)	-1.2E-05 (-0.84)	0.352 (2.46)	-0.007 (-1.58)	0.048 (4.11)
$\gamma * g * J1$	-0.173 (-5.04)	-0.184 (-5.13)	-0.174 (-5.33)	-5.3E-05 (-1.15)	-0.181 (-0.45)	-0.004 (-0.69)	-0.171 (-4.89)
$\gamma * g * J2$	-0.039 (-2.43)	-0.050 (-2.90)	-0.039 (-2.63)	-6.0E-05 (-1.55)	0.063 (0.33)	-0.011 (-1.44)	-0.044 (-2.84)
$\gamma * g * J3$	-0.023 (-1.71)	-0.034 (-2.35)	-0.035 (-2.60)	-9.6E-06 (-0.41)	0.020 (0.13)	0.000 (0.24)	-0.032 (-1.91)
$\gamma * g * J4$	-0.038 (-2.56)	-0.048 (-3.15)	-0.052 (-3.26)	4.1E-06 (0.21)	0.068 (0.30)	-0.007 (-5.45)	-0.056 (-3.78)
$\gamma * g * XE$	-0.126 (-6.61)	-0.126 (-6.61)	-0.122 (-6.29)	-4.8E-06 (-0.14)	-0.507 (-1.61)	0.007 (2.09)	-0.133 (-6.98)
$\gamma * g * NYE$	-0.263 (-3.85)	-0.263 (-3.85)	-0.235 (-3.30)	-1.2E-04 (-1.96)	-0.895 (-1.25)	-0.008 (-8.61)	-0.277 (-4.48)
g	-0.001 (-7.52)	0.000 (-2.48)	0.000 (-2.71)		-0.004 (-4.55)		-0.001 (-8.34)
$g * trend$		-1.6E-05 (-2.85)					
$\ln(ME)$	-0.006 (-5.22)	-0.007 (-5.53)	-0.007 (-5.92)		0.000 (-0.20)		
$\ln(BM)$	0.009 (2.50)	0.011 (3.17)	0.005 (1.69)		-0.003 (-1.21)		
$\ln(ME) * J$	-0.008 (-8.86)	-0.008 (-8.87)	-0.008 (-8.81)		0.001 (0.41)		
$r_{-1:0}$							-0.003 (-6.02)
$r_{-12:-1}$							0.000 (4.46)
$r_{-36:-12}$							0.000 (-2.00)
V							-0.001 (-3.03)
$\ln(ME)$							-0.007 (-5.72)

Panel C				
	1963-2008	1954-1980	1980-2008	1993-2008
	(1)	(2)	(3)	(4)
γ^*g^*FN	0.008 (2.14)	0.002 (0.32)	0.002 (0.34)	-0.049 (-4.24)
γ^*g^*D1	0.036 (2.26)	0.043 (2.69)	0.021 (1.14)	0.034 (1.00)
γ^*g^*D2	0.029 (1.42)	0.047 (3.91)	0.006 (0.27)	-0.002 (-0.08)
γ^*g^*D3	0.055 (4.68)	0.025 (2.77)	0.065 (3.36)	0.169 (2.07)
γ^*g^*D4	0.045 (4.46)	0.040 (3.04)	0.036 (2.59)	0.064 (1.42)
γ^*g^*J1	-0.169 (-5.02)	-0.201 (-6.67)	-0.165 (-3.30)	-0.516 (-15.01)
γ^*g^*J2	-0.037 (-2.33)	-0.046 (-3.38)	-0.042 (-1.70)	-0.201 (-2.00)
γ^*g^*J3	-0.021 (-1.61)	-0.042 (-2.49)	-0.020 (-1.24)	-0.142 (-3.58)
γ^*g^*J4	-0.037 (-2.48)	-0.076 (-3.24)	-0.028 (-1.84)	-0.111 (-3.64)
γ^*g^*XE	-0.124 (-6.63)	-0.109 (-4.09)	-0.139 (-5.28)	-0.192 (-2.39)
γ^*g^*NYE	-0.262 (-3.84)	-0.320 (-8.45)	-0.222 (-2.33)	-0.845 (-3.80)
g	-0.001 (-7.57)	0.000 (-0.94)	-0.001 (-6.32)	0.000 (-1.75)
$\ln(ME)$	-0.007 (-5.31)	-0.007 (-3.48)	-0.007 (-4.68)	-0.017 (-6.74)
$\ln(BM)$	0.013 (3.34)	-0.002 (-0.40)	0.016 (3.21)	0.003 (1.29)
$\ln(ME)^*J$	-0.009 (-8.67)	-0.010 (-7.11)	-0.008 (-6.38)	-0.006 (-3.94)

Table III: Pooled Return Regression Estimates: 1954-2008

We report the results from pooled regressions of day t stock returns on $t - 1$ characteristics using U.K. data. Characteristics are measured on a weekly basis for conciseness. All firm-specific variables, defined in Table I but computed with U.K. data, are cross-sectionally demeaned, and when appropriate, interacted with our proposed tax-selling premium variable γ , defined in Table II but computed with U.K. data, along with monthly or weekly dummy variables. The dummy variables are RoY and $UK(X)$ for the rest of the tax year and specific weeks of the tax year respectively, with X representing the week of the tax year. Since the end of the tax year in the U.K. is the 5th of April, we define these weeks in relation to the end of the tax year. Therefore, the last week of the year is in effect the last 5 days before the end of the tax year, including days in April and March potentially. T -statistics (in parentheses) are robust to cross-correlation in the residuals using the clustered standard errors of Rogers (1983, 1993). The sample starts in January 1996 and ends in December 2008. The full specification of the regression takes the form

$$\begin{aligned}
r_{i,t} = & a_1\gamma_{t-1}g_{i,t-1}RoY \\
& + a_2\gamma_{t-1}g_{i,t-1}UK49 + a_3\gamma_{t-1}g_{i,t-1}UK50 + a_4\gamma_{t-1}g_{i,t-1}UK51 + a_5\gamma_{t-1}g_{i,t-1}UK51 \\
& + a_6\gamma_{t-1}g_{i,t-1}UK1 + a_7\gamma_{t-1}g_{i,t-1}UK2 + a_8\gamma_{t-1}g_{i,t-1}UK3 + a_9\gamma_{t-1}g_{i,t-1}UK4 \\
& + a_{10}\ln ME_{i,t-1} + a_{11}\ln BM_{i,t-1} + a_{12}r_{i,-1:0} + a_{13}r_{i,-12:-1} + a_{14}r_{i,-36:-12} + \varepsilon_{i,t}.
\end{aligned}$$

	(1)	(2)
$\gamma * g * RoY$	0.032 (1.58)	0.041 (1.71)
$\gamma * g * UK49$	0.131 (2.02)	0.142 (2.14)
$\gamma * g * UK50$	0.176 (2.30)	0.187 (2.38)
$\gamma * g * UK51$	0.058 (0.40)	0.068 (0.47)
$\gamma * g * UK52$	0.050 (0.61)	0.061 (0.72)
$\gamma * g * UK1$	-0.124 (-1.41)	-0.112 (-1.28)
$\gamma * g * UK2$	-0.231 (-2.47)	-0.221 (-2.33)
$\gamma * g * UK3$	-0.223 (-2.34)	-0.212 (-2.20)
$\gamma * g * UK4$	-0.079 (-1.44)	-0.067 (-1.19)
$\ln(ME)$		0.000 (1.71)
$\ln(BM)$		0.045 (1.50)
$r_{-1:0}$		0.000 (0.07)
$r_{-12:-1}$		0.001 (1.18)
$r_{-36:-12}$		-0.001 (-2.69)

Table IV: Pooled Selling Pressure Regression Estimates: 1993-2005

We report the results from pooled regressions of the day t change in (or level of) selling pressure (for either small or large sized trades) on $t - 1$ characteristics. Characteristics are measured on a weekly basis for conciseness. Panel A reports results with the level of selling pressure, while Panel B shows results with the change in that level. In both cases, we split the sample into small and large trades. All firm-specific variables, defined in Table I, are cross-sectionally demeaned, and when appropriate, then interacted with our tax-selling premium variable, γ , and with dummy variables corresponding to different periods of the year. These dummy variables as well as γ are defined in Table II. T -statistics (in parentheses) are robust to simultaneous correlation both across firms and across years based on the method developed by Thompson (forthcoming). The sample starts in February of 1993 and ends in January 2005. The specifications of these regressions are consistent with regression (5) of Panel B Table II and take the form

$$\begin{aligned}
 Sell_{i,t} = & a_1\gamma_{t-1}g_{i,t-1}FN \\
 & + a_2\gamma_{t-1}g_{i,t-1}D1 + a_3\gamma_{t-1}g_{i,t-1}D2 + a_4\gamma_{t-1}g_{i,t-1}D3 + a_5\gamma_{t-1}g_{i,t-1}D4 \\
 & + a_6\gamma_{t-1}g_{i,t-1}J1 + a_7\gamma_{t-1}g_{i,t-1}J2 + a_8\gamma_{t-1}g_{i,t-1}J3 + a_9\gamma_{t-1}g_{i,t-1}J4 \\
 & + a_{10}\gamma_{t-1}g_{i,t-1}XE + a_{11}\gamma_{t-1}g_{i,t-1}NYE + a_{12}g_{i,t-1} \\
 & + a_{13}r_{i,-1:0} + a_{14}r_{i,-12:-1} + a_{15}r_{i,-36:-12} + a_{16}V + a_{17}\ln ME_{i,t-1} + \varepsilon_{i,t},
 \end{aligned}$$

$$\begin{aligned}
 Sell_{i,t} - Sell_{i,t-1} = & a_1\gamma_{t-1}g_{i,t-1}FN \\
 & + a_2\gamma_{t-1}g_{i,t-1}D1 + a_3\gamma_{t-1}g_{i,t-1}D2 + a_4\gamma_{t-1}g_{i,t-1}D3 + a_5\gamma_{t-1}g_{i,t-1}D4 \\
 & + a_6\gamma_{t-1}g_{i,t-1}J1 + a_7\gamma_{t-1}g_{i,t-1}J2 + a_8\gamma_{t-1}g_{i,t-1}J3 + a_9\gamma_{t-1}g_{i,t-1}J4 \\
 & + a_{10}\gamma_{t-1}g_{i,t-1}XE + a_{11}\gamma_{t-1}g_{i,t-1}NYE + a_{12}g_{i,t-1} \\
 & + a_{13}r_{i,-1:0} + a_{14}r_{i,-12:-1} + a_{15}r_{i,-36:-12} + a_{16}V + a_{17}\ln ME_{i,t-1} + \varepsilon_{i,t}.
 \end{aligned}$$

	Panel A			Panel B		
	all (1)	small (2)	large (3)	all (1)	small (2)	large (3)
$\gamma * g * FN$	-0.001 (-0.01)	-0.080 (-0.48)	-0.799 (-3.98)	-0.020 (-1.29)	-0.027 (-1.6)	-0.013 (-0.44)
$\gamma * g * D1$	-0.946 (-4.67)	-1.165 (-4.75)	-1.201 (-4.26)	-0.126 (-1.42)	-0.146 (-2.02)	0.015 (0.12)
$\gamma * g * D2$	-0.965 (-6.93)	-1.304 (-5.8)	-1.151 (-7.11)	-0.040 (-0.77)	-0.081 (-1.7)	0.002 (0.02)
$\gamma * g * D3$	-1.380 (-8.88)	-1.608 (-7.52)	-1.859 (-10.54)	-0.141 (-1.97)	-0.142 (-1.96)	-0.225 (-1.5)
$\gamma * g * D4$	-1.893 (-11.18)	-1.965 (-9.36)	-2.241 (-9.84)	-0.176 (-3.03)	-0.079 (-1.71)	-0.233 (-1.5)
$\gamma * g * J1$	1.718 (4.18)	1.650 (3.96)	1.035 (2.72)	0.487 (3.27)	0.421 (2.73)	0.242 (2.15)
$\gamma * g * J2$	0.966 (5.93)	0.875 (5.4)	0.055 (0.37)	-0.089 (-1.17)	-0.045 (-0.59)	-0.181 (-2.98)
$\gamma * g * J3$	0.747 (4.5)	0.713 (3.67)	-0.250 (-1.16)	0.107 (3.37)	0.048 (1.56)	0.214 (3.95)
$\gamma * g * J4$	0.587 (3.86)	0.543 (2.66)	-0.194 (-0.81)	0.066 (1.14)	0.080 (1.54)	0.148 (1.59)
$\gamma * g * XE$	0.390 (2.6)	0.207 (1.71)	1.173 (4.29)	0.090 (0.46)	0.006 (0.04)	0.954 (4.01)
$\gamma * g * NYE$	0.230 (1.51)	0.593 (4.22)	0.198 (0.74)	0.521 (4.2)	0.675 (4.71)	0.660 (1.5)
g	-0.001 (-1.88)	-0.001 (-2.4)	0.007 (3.69)	0.000 (-0.41)	0.000 (-0.72)	0.000 (-0.89)
$r_{-1;0}$	-0.008 (-3.95)	0.003 (1.03)	-0.010 (-4.78)	0.012 (7.2)	0.011 (8.32)	0.012 (7.49)
$r_{-12;-1}$	-0.002 (-1.61)	-0.005 (-2.29)	0.000 (-0.16)	0.000 (1.54)	0.000 (2.14)	0.000 (2.26)
$r_{-36;-12}$	-0.001 (-1.16)	-0.003 (-2.84)	0.001 (1.58)	0.000 (0.4)	0.000 (-0.05)	0.000 (-0.32)
V	-0.060 (-4.55)	-0.018 (-1.65)	-0.071 (-7.61)	0.000 (0.7)	0.001 (0.93)	-0.001 (-1.17)
$\ln(ME)$	-1.666 (-13.33)	-1.410 (-10.48)	-1.495 (-12.32)	0.031 (6.91)	0.029 (8.53)	0.012 (1.66)

Table V: Aggregate Time-Series Regression Estimates: 1954-2008

We report the results from monthly regressions forecasting the excess return on the market portfolio with our tax-selling premium variable, γ , defined in Table 2 and the value-weight average, g_M , of the firm-level capital gains overhang, g , defined in Table I. We also include in these regression the value-weight average, BM_M , of the firm-level book-to-market ratio, BM , also defined in Table I. The sample starts in February of 1954 and ends in December 2008. The regression specification that includes the union of all of the independent variables we consider would be

$$\begin{aligned}
 RMRF_t = & a_0 + a_1\gamma_{t-1}g_{M,t-1}FN + a_2\gamma_{t-1}g_{M,t-1}D + a_3\gamma_{t-1}g_{M,t-1}J \\
 & + a_4g_{M,t-1}FN + a_5g_{M,t-1}D + a_6g_{M,t-1}J \\
 & + a_7\gamma_{t-1}FN + a_8\gamma_{t-1}D + a_9\gamma_{t-1}J + a_{10}BM_{M,t-1} + \varepsilon_{i,t}.
 \end{aligned}$$

<i>Int.</i>	$\gamma * g_M$			g_M			γ			BM_M	R^2
	FN	D	J	FN	D	J	FN	D	F		
-0.761 (-1.63)	0.426 (0.63)	1.406 (0.86)	-3.742 (-2.04)							0.771 (1.64)	0.012
-0.797 (-1.71)	-1.304 (-1.20)	-2.155 (-0.76)	-7.359 (-2.16)	0.052 (2.18)	0.104 (1.66)	0.098 (1.38)				0.804 (1.71)	0.025
-1.263 (-2.48)	0.612 (0.89)	1.012 (0.60)	-5.550 (-2.81)				-0.438 (-2.93)	-0.169 (-0.60)	0.255 (0.86)	1.283 (2.50)	0.031

Table VI: Portfolio Time-Series Regression Estimates: 1954-2008

We report the results from monthly regressions forecasting the CAPM alpha for four factor portfolios using the portfolio-specific tax-selling capital gains overhang. *RMRF* is the excess return on the market portfolio. We form the low-minus-high-overhang portfolio, *TAX*, by going long a value-weight portfolio of the bottom twenty percent of stocks and short a value-weight portfolio of the top twenty percent of stocks, in each case based on NYSE breakpoints. *HML* (high minus low book-to-market) and *SMB* (small minus big size) portfolio returns are constructed as in Fama and French (1993). We construct our momentum portfolio in the same way Ken French constructs his *UMD* portfolio. Our measurement of each factor's capital gains overhang comes from portfolios that only include stocks that have capital gains overhang data available. However, we forecast the returns on the factors that are available from Ken French's website. We interact *RMRF* with our measure of the market's capital gains overhang, g_M , described in Table V. Dummy variables corresponding to periods of the year as well as our tax-selling premium variable, γ , are also included in the interactions. These dummy variables as well as γ are defined in Table II. The time-series of the *RMRF* interaction, $\gamma * g_M$, is standardized to aid interpretability. The sample starts in February of 1954 and ends in December 2008.

	Panel A: TAX			Panel B: HML		
	(1)	(2)	(3)	(1)	(2)	(3)
<i>Intercept * FN</i>	-0.027 (-14.32)	-0.027 (-14.70)	-0.028 (-10.32)	0.002 (2.59)	0.002 (2.55)	0.003 (1.96)
<i>Intercept * D</i>	-0.037 (-6.07)	-0.032 (-4.99)	-0.031 (-3.46)	0.003 (1.00)	0.003 (0.97)	0.000 (0.06)
<i>Intercept * J</i>	0.030 (4.95)	0.025 (4.12)	0.009 (0.96)	0.015 (4.94)	0.013 (4.35)	0.012 (2.71)
$\gamma * g * FN$			-0.036 (-0.28)			0.019 (0.30)
$\gamma * g * D$			0.038 (0.11)			-0.158 (-0.88)
$\gamma * g * J$			-1.124 (-2.37)			-0.055 (-0.23)
<i>RMRF * FN</i>		0.284 (6.35)	0.285 (6.37)		-0.165 (-7.38)	-0.165 (-7.37)
<i>RMRF * D</i>		0.004 (0.02)	0.002 (0.01)		-0.159 (-1.77)	-0.149 (-1.64)
<i>RMRF * J</i>		0.261 (2.08)	0.224 (1.77)		-0.142 (-2.27)	-0.144 (-2.28)
$\gamma * g_M * RMRF * FN$		-0.025 (-1.03)	-0.026 (-1.05)		0.022 (1.84)	0.023 (1.86)
$\gamma * g_M * RMRF * D$		-0.395 (-2.41)	-0.387 (-2.14)		-0.086 (-1.05)	-0.120 (-1.32)
$\gamma * g_M * RMRF * J$		0.382 (6.08)	0.268 (3.38)		0.090 (2.87)	0.084 (2.13)
<i>RMRF</i>	0.297 (7.15)			-0.163 (-8.07)		
R^2	0.32	0.35	0.37	0.12	0.13	0.13

	Panel C: SMB			Panel D: UMD		
	(1)	(2)	(3)	(1)	(2)	(3)
<i>Intercept * FN</i>	0.000 (0.11)	0.000 (0.00)	0.001 (0.85)	0.009 (5.57)	0.008 (5.53)	0.008 (3.73)
<i>Intercept * D</i>	0.002 (0.47)	0.003 (0.90)	0.008 (1.54)	0.020 (4.02)	0.017 (3.28)	0.014 (1.95)
<i>Intercept * J</i>	0.021 (5.70)	0.019 (5.16)	0.007 (1.23)	-0.016 (-3.33)	-0.014 (-2.86)	-0.006 (-0.82)
$\gamma * g * FN$			0.090 (1.17)			-0.010 (-0.10)
$\gamma * g * D$			0.272 (1.27)			-0.152 (-0.52)
$\gamma * g * J$			-0.837 (-2.95)			0.555 (1.43)
<i>RMRF * FN</i>		0.127 (4.75)	0.125 (4.69)		-0.067 (-1.85)	-0.067 (-1.84)
<i>RMRF * D</i>		0.015 (0.14)	-0.003 (-0.03)		0.042 (0.28)	0.052 (0.35)
<i>RMRF * J</i>		0.056 (0.74)	0.028 (0.37)		-0.019 (-0.19)	-0.001 (-0.01)
$\gamma * g_M * RMRF * FN$		0.032 (2.20)	0.034 (2.30)		0.074 (3.75)	0.074 (3.73)
$\gamma * g_M * RMRF * D$		-0.177 (-1.80)	-0.119 (-1.11)		0.356 (2.66)	0.324 (2.20)
$\gamma * g_M * RMRF * J$		0.162 (4.31)	0.077 (1.64)		-0.207 (-4.05)	-0.151 (-2.33)
<i>RMRF</i>	0.114 (4.64)			-0.091 (-2.70)		
R^2	0.08	0.12	0.15	0.09	0.11	0.12

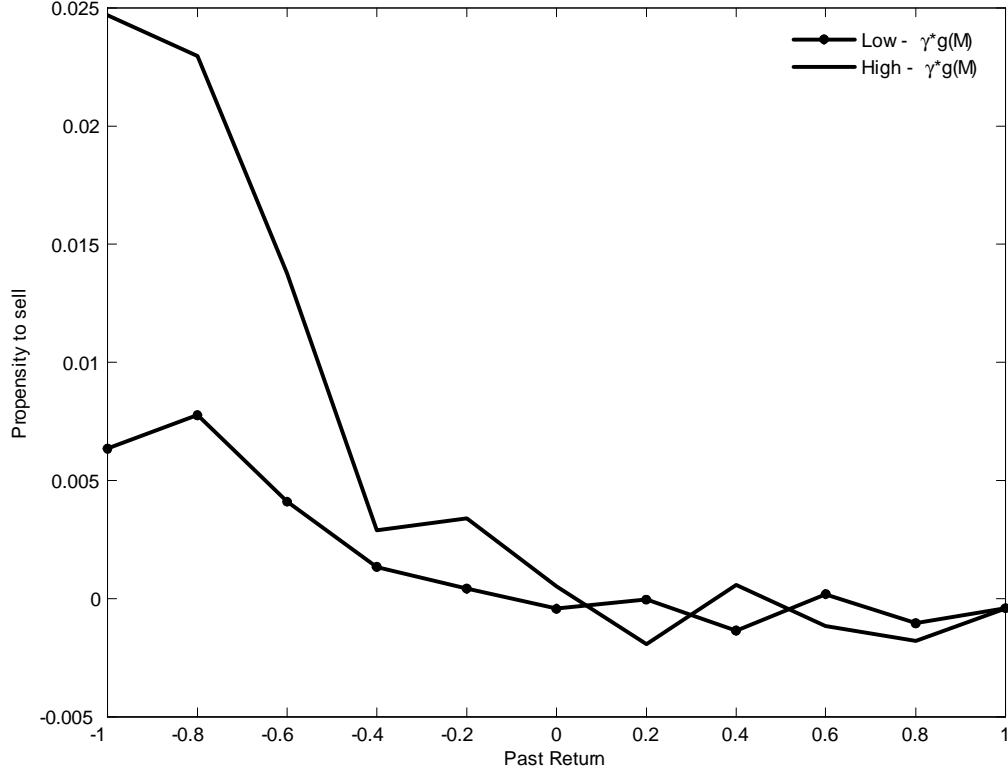


Figure 1: This figure shows the propensity of taxable investor to sell winners and losers at the turn of the year using the dataset studied in Odean (1998). For each stock in the dataset, we calculate a unrealized capital gain/loss from the time the investor purchased the stock until it was eventually sold. For each of eleven evenly-spaced bins ranging from -100% to > 100%, we compare these unrealized gains and losses to observed gains and losses. We then plot the difference in the percentage of realized gains and losses in December versus January, where the percentage is averaged over each return bucket. The data is split into years that are predicted to have either a low or a high tax-selling propensity for the market portfolio, $-\gamma * g(M)$, as discussed in the paper. The solid-dotted line represents the December propensity minus the January propensity for the years where the tax-selling propensity is predicted to be low and the solid line represents the December propensity minus the January propensity for the years where the tax-selling propensity is predicted to be high.

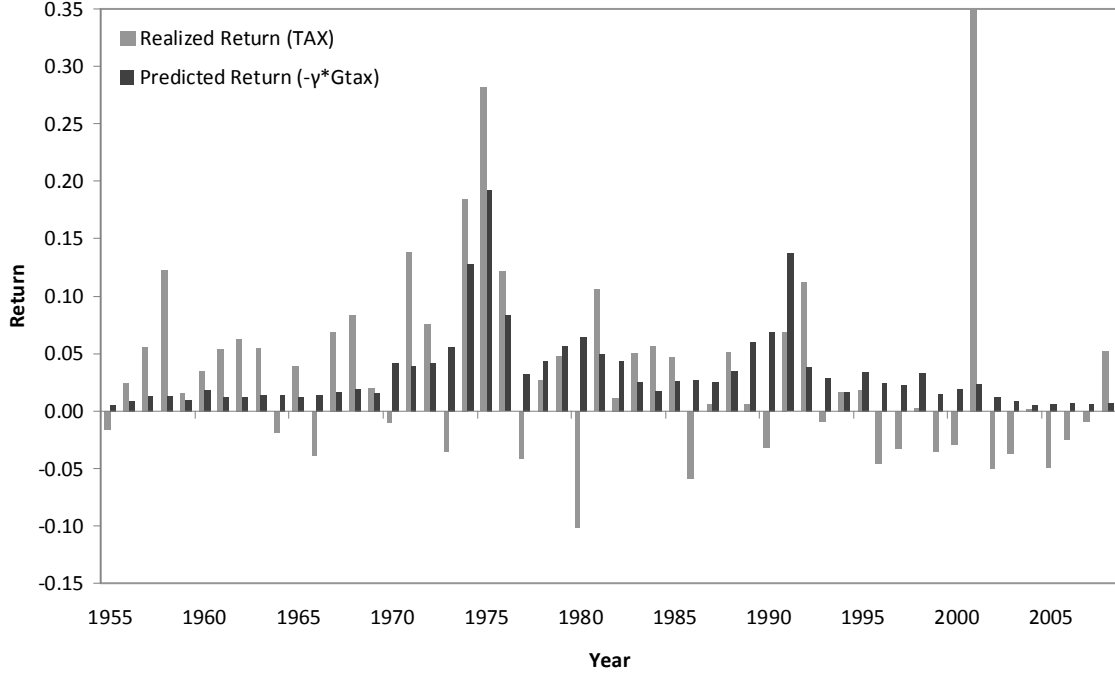


Figure 2: This figure plots the realized January returns on our TAX factor over the course of the sample. To form TAX, each month we sort all NYSE stocks on our overhang measure and calculate 20th and 80th percentile breakpoints. We then buy all NYSE-AMEX-NASDAQ stocks that are below the NYSE 20th percentile and sell all NYSE-AMEX-NASDAQ stocks that are above the NYSE 80th percentile. The positions in the long and short sides are value-weight. In each bin, we plot next to the realized January return, our forecast of the expected January rebound based on the product of i) our tax-selling premium variable, γ , defined in Table II and ii) the net overhang for the TAX factor, g_{TAX} . That forecast comes from the regression, $TAX_{JAN,t} = a_0 + a_1 \gamma_{t-1} g_{TAX,t-1} + \varepsilon_{JAN,t}$. The estimate of a_0 is 0.00192 (t-statistic of 0.14), the estimate of a_1 is -1.99 (t-statistic of -3.52), and the adjusted R^2 is 17.7%.

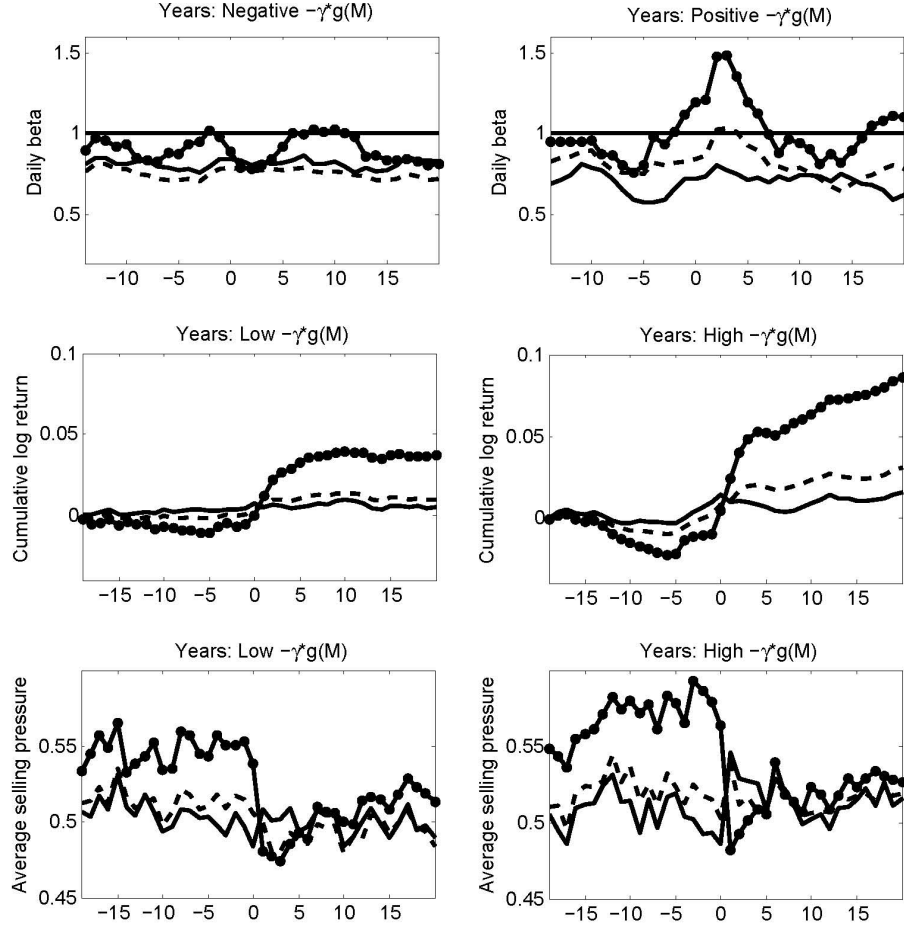


Figure 3: This figure graphs various characteristics of selected capital-gains-overhang quintile portfolios in the days surrounding the turn of the year. For all graphs, the solid line represents the highest overhang quintile, the dashed line is the middle overhang quintile, and solid dotted line is the lowest overhang quintile portfolio. On the x axis, 0 represents the last trading day in December and 1 represents the first trading day in January. The top two graphs in this figure show daily betas for these portfolios, where daily beta is a five-day rolling beta estimate (as explained in Section 3.3). The left (right) graph plots rolling daily beta conditional on a predicted negative (positive) January rebound as determined by $-\gamma * g(M)$. The middle two graphs in this figure show cumulative log returns for these portfolios. The left (right) graph plots cumulative returns for those time periods where the market's January rebound is predicted to be below-median (above-median). The bottom two graphs in this figure show the selling pressure for these portfolios, where selling pressure is the ratio of sell trades relative to all trades. Therefore, the left (right) panel graphs the average selling pressure for those time periods where the market's January rebound is predicted to be below-median (above-median).