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The pricing of firms with expected losses/profits: The role of January

Abstract

We examine the role of January in the relation between expected losses/profits and future stock returns. We predict and find that the relation between expected losses/profits and future returns reverses from the usual positive relation in non-January months to a negative one in January. The reverse January relation is consistent across sample years, is observed in the United States and international markets, and is incremental to other variables associated with January returns. At least part of the reverse January relation is explained by tax-loss selling. Further analysis shows that the reverse January relation results in a temporary *price drift away from fundamental value*. In other words, we find that abnormal positive (negative) future returns do not always indicate past under(over)valuation. Overall, our results illustrate the importance of controlling for the effect of January when examining how investors price expected losses/profits.

1. Introduction

Since the seminal paper by Ball and Brown (1968), the relation between earnings and stock prices has been at the center of capital markets research. While the efficient market hypothesis predicts that stock price fully reflects all publicly available information about expected future earnings, empirical research finds that stocks with low (high) expected earnings earn low (high) future risk-adjusted returns.[1] The return drift is especially large for firms with past and expected future losses.[2] Much of the prior research has focused on different measures of firm performance to document the return drift. In this study, we argue that another important stock price phenomenon—the January effect—plays an important role in pricing of expected earnings, especially expected losses. We predict and find that the expected loss/profit drift reverses in January.

The January or turn-of-the-year effect refers to abnormally high returns earned by stocks, especially stocks of small firms, during the month of January.[3] The most common explanation of the January effect is tax-loss selling. According to this explanation, in order to minimize tax liability, tax-sensitive investors—such as individual investors—sell losing stocks before year-end

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[1] Elgers et al. (2001) show that the ratio of analysts' annual earnings forecast level to stock price predicts future returns over the next twelve months. Frankel and Lee (1998) show that the value-to-price ratio based on earnings forecast levels predict future returns over the next three years. Balakrishnan et al. (2010) find that firms with past losses (profits)—which can be viewed as expected losses (profits) under a simple random walk model—earn low (high) future abnormal stock returns. Research finds that expected losses are associated with low future returns in the US (Li 2011), the UK (Jiang, et al. 2016), and Australia (Wu 2016). Cen et al. (2013) show that firms with forecasted earnings per share lower (higher) than the industry median earn abnormally high (low) future stock returns. The magnitude of abnormal returns documented in these studies often exceeds 10% per year.

[2] Balakrishnan et al. (2010) show that firms with extreme losses (profits) earn an abnormal return of approximately -6% (+4%) over 120 trading days following the earnings announcement day. Li (2011) shows that firms with expected persistent losses earn 10.4% lower abnormal one-year returns than loss firms that are more likely to return to profitability. Jiang et al. (2016) show that future abnormal returns associated with expected losses are concentrated in months of subsequent earnings announcements and greater for stocks with higher trading costs.

[3] Rozeff and Kinney (1976), Keim (1983), Reinganum (1983), Blume and Stambaugh (1983), and Thaler (1987).

and then buy them back in January.[4] The positive price pressure in January leads to positive abnormal returns in that month. Several studies find evidence consistent with the tax-loss selling explanation. Poterba and Weisbenner (2001) show that changes in the tax rules for capital gains explain changes in January returns. Kang, et al. (2015) show that the turn-of-the-year tax-selling pressure is stronger when interest rates are high and therefore the cost of delaying tax-selling benefits is high. Sias and Starks (1997) find that stocks with greater individual investor interest earn higher (lower) returns in January (December) relative to stocks with greater institutional investor interest. Ritter (1988), Badrinath and Lewellen (1991), and Dyl and Maberly (1992) show that tax-motivated trading by individual investors is associated with January returns. Sikes (2014) show that in addition to individual investors, institutional investors with strong tax incentives also exhibit tax-loss selling trading behavior which contributes to the January effect. Starks et al. (2006) find that the trading behavior of tax-sensitive investors explains the January effect in municipal bond closed-end funds.[5]

Tax-loss selling and therefore the January effect should be important for firms with poor financial performance such as stocks with expected negative earnings. Prior studies argue that the January effect is strong for small firms because they are more likely to have periods of poor operating and stock return performance and therefore are more likely to bring capital losses to some investors (Roll 1983; Reinganum 1983). Since expected negative earnings are also likely to

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[4] The time between a stock sale and repurchase must be greater than 30 days to avoid a wash sale. Losses from trades of securities in a wash sale cannot be deducted under Internal Revenue Service rules. Following prior studies, we refer to this tax-motivated selling (buying) before (after) year-end as tax-loss selling.

[5] The January effect has also been observed in countries with a non-December tax year-end and in countries with no taxes on capital gains, which may suggest that tax-loss selling is not the sole explanation (Gultekin and Gultekin 1983; Berges et al. 1984; Kato and Schallheim 1985; Thaler 1987; Lee 1992; Ko 1998). At the same time, as Thaler (1987) notes “Still, returns are high in April in Great Britain, and in July in Australia, so taxes do seem to be part of the story.” Also, tax-loss selling by investors from the US and other countries with taxes on capital gains and a December tax year-end could result in the January effect in such countries (Berges et al. 1984; Kato and Schallheim 1985).

lead to poor stock performance and capital losses during the current year, tax-loss selling should also be evident for such firms.[6] Further, since the price pressure induced by tax-loss selling behavior is large and concentrated in one month, we expect the January effect to dominate (during that month) the documented expected loss/profit drift.[7] We therefore predict that firms with expected losses will earn higher January returns than will firms with expected profits.[8] As a result, the usual positive relation between expected losses/profits and future stock returns will reverse to a negative relation in January. The predicted reversal is markedly different from a usual combination of two anomalies—such as the size effect and the January effect—wherein the abnormal returns are enhanced, not reversed.

An important implication of the January reversal is that it can result in underestimation of the loss/profit drift during the whole year or even make it appear insignificant. Consequently, in a study that uses cumulative returns that include both January and non-January months, stock prices will appear more efficient than they actually are. In particular, abnormal returns earned by trading strategies based on expected losses/profits can be significantly enhanced by reversing the long/short strategy during the month of January.

In the empirical analysis, we use analysts' earnings forecasts to measure expected losses/profits. Our sample consists of 1.193 million firm-month observations with analyst forecast data from I/B/E/S and spans the period from June 1982 through December 2011. We use a simple

[6] Although capital losses refer to investors' losses in the financial market, it is difficult to measure these losses directly based on past stock returns because any given stock was purchased and sold at various points in time by different investors (Roll 1983). Therefore, past returns will not fully explain the effects of size and negative earnings.

[7] The typical increase in monthly stock return due to the January effect exceeds three percent while the typical monthly hedge return due to loss/profit drift is around one percent.

[8] Although, firms with expected profits will have lower tax-loss selling than firms with expected losses, the likelihood of tax-loss selling for these stocks is still positive. Therefore, even firms with expected profits will have somewhat higher returns in January than in non-January months. Our empirical findings are consistent with this prediction.

binary measure that divides firms into two groups: firms with negative earnings forecasts (the expected loss (EL) portfolio) and firms with non-negative earnings forecasts (the expected profit (EP) portfolio). Earnings forecasts are analyst consensus forecasts of annual earnings for the nearest fiscal year for which earnings have not yet been announced.[9] We focus on earnings sign and particularly losses because tax-loss selling is likely to affect these stocks most. The focus on earnings sign also has the advantage of avoiding any issues related to the choice of the scaling variable.[10] We use annual rather than quarterly earnings forecast since tax-loss selling is more likely to be important for stocks that experience poor financial performance over a relatively long period of time such as a year.[11]

Similar to the average positive return predictability documented by prior research, we find that EL firms earn a 1.22% lower future monthly return than EP firms in non-January months. In contrast, we find that EL firms earn a 3.88% *higher* future monthly return than EP firms in January. Thus, the expected loss/profit drift reverses to a negative one in January. The resulting reverse January relation is economically large and consistent across sample years and various types of stocks.[12] Consistent with the tax-loss selling hypothesis, the reversal is driven by loss firms rather than profit firms. Further analysis shows that the reverse January relation is robust to using earnings forecasts measured at different calendar months, using a continuous measure of expected

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[9] For example for firms with a typical December fiscal year-end, an annual earnings forecast issued in December 2010 relates to earnings for 2010. By the time the December consensus forecast is issued, earnings for the first three quarters are known and earnings for the fourth quarter is forecasted. Since the forecast primarily relates to the current calendar year, forecasted loss is likely to lead to the tax-loss selling behavior.

[10] The sensitivity of results in capital market research to the choice of the scale variable has been documented by many studies (Brown et al. 1999; Easton and Sommers 2003; Durtschi and Easton 2005, 2009; Barth and Clinch 2009; Barth and Kallapur 1996; Burgstahler and Chuk 2015).

[11] In a concurrent study, Byard, et al. (2017) examine why some loss firms receive greater analyst coverage than other loss firms and find that analyst following is greater for loss firms that have better future prospects. While Byard et al. examine analysts' ex ante incentives to follow firms with current losses, our paper examines firms with expected losses as represented by analysts' consensus forecast and the role of January on the mispricing of these stocks.

[12] Specifically, the reverse January relation is significant for small and medium stocks, for growth, neutral, and value stocks, and for stocks with low, medium, and high past returns.

earnings instead of the expected loss/profit indicator, and using realized earnings as a measure of expected earnings under a simple random walk model. We find that the reverse January relation also holds in other countries that have taxes on capital gains and a December tax year-end. Furthermore, the reverse January relation in the international sample fully offsets the positive relation in non-January months, thereby leading to an insignificant relation for the entire calendar year. This finding shows that using cumulative returns which include both January and non-January months and which ignore the January reversal could lead to the erroneous conclusion that there is no relation between expected losses/profits and future returns.

An analysis of the January effect on the expected loss/profit drift vis-à-vis the January effects for variables examined by prior research (firm size, CAPM beta, book-to-market ratio, momentum, stock price level, return volatility, and accruals quality) reveals the following. First and most importantly, the expected loss/profit drift is the only one that reverses the direction in January. The return predictability of other variables becomes stronger or stays the same in January.[13] Second, while other variables explain about half of the EL/EP reverse January relation, the incremental effect of expected losses/profits remains significant. Finally, the economic effect of expected losses/profits in January is greater than that of all other variables except stock price level.

Next, we test and find support for the prediction that the reverse January relation is at least partly caused by the turn-of-the-year tax-loss selling by individual investors. Specifically, the magnitude of the reverse January relation is increasing in the likelihood of tax-loss selling,[14] and

[13] Although momentum reverses in January, the reverse January relation for momentum disappears when controlling for other variables, including expected losses/profits.

[14] The likelihood of tax-loss selling is proxied by (i) the stock price decline relative to the maximum stock price over the year (Reinganum 1983; Chang and Pinegar 1986; Mashruwala and Mashruwala 2011) and (ii) the negative of the buy-and-hold return over the year (Sias and Starks 1997; Poterba and Weisbenner 2001; Mashruwala and Mashruwala 2011).

the effect of tax-loss selling on the reverse January relation is observed only for firms with low institutional ownership. We also find that a significant part of the reverse January relation is caused by stocks with low expected earnings or expected losses, which is consistent with the argument that tax-loss selling behavior is more likely for these stocks. In contrast, we do not find evidence that the information hypothesis and window dressing by institutional investors explain the reverse January relation.[15]

Further, we predict and find that the reverse January relation is decreasing with the likelihood of loss reversal.[16] The finding is consistent with the argument that compared to losses that are expected to persist, losses that are expected to reverse in the near future are less likely to result in capital losses and tax-loss selling behavior.

Finally, we examine the implication of the reverse January relation for firm under(over)valuation. We measure firms' under(over)valuation using (i) stock returns around future earnings announcements and (ii) fundamental-value-to-price ratios (Lee et al. 1999). Usually, future abnormal returns represent the correction of preexisting mispricing. We do find that EP and EL firms are mispriced (under- and overvalued, respectively). However, the documented January effect does not correct the mispricing but exacerbates it. In other words, we

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[15] The window-dressing hypothesis proposes that portfolio managers sell loser stocks and buy winner stocks at the end of the year to make their portfolios look better for fund investors. Although some studies find evidence consistent with this hypothesis (Ng and Wang 2004), most studies testing the window-dressing hypothesis vis-à-vis the tax-loss selling hypothesis tend to support the latter (Sias and Starks 1997; Poterba and Weisbenner 2001; Grinblatt and Moskowitz 2004; Sikes 2014). The information hypothesis argues that since most firms have December fiscal year-ends, abnormal January returns are driven by greater uncertainty and/or information flow around fiscal year-end (Rozeff and Kinney 1976). Studies testing the information hypothesis vis-à-vis the tax-loss selling hypothesis tend to support the tax-loss selling explanation (Brauer and Chang 1990).

[16] The likelihood of loss reversal is proxied by the firm's return on assets; firm size; an indicator that the loss is the first in a sequence; the number of losses in the loss sequence; an indicator that the firm pays dividends; and an indicator that the firm stops paying dividends in the current year (Joos and Plesko 2005).

find that the reverse January relation results in a temporary *price drift away from fundamental value*.[17]

Our study contributes to the literature in several ways. First, the paper contributes to the literature on the mispricing of expected losses/profits. Prior research shows that at least part of the mispricing can be traced to investors' cognitive biases in estimating future profitability of the firm and that the mispricing is concentrated among firms with persistent expected losses (Balakrishnan et al. 2010; Li 2011; Cen et al. 2013; Jiang et al. 2016; Wu 2016).[18] In this paper, we show that tax-loss selling is another important source of the mispricing, which has not been appreciated by the extant literature. Specifically, tax-loss selling behavior for stocks with expected losses leads to positive abnormal January returns resulting in greater overvaluation which is then followed by lower returns in subsequent months. The abnormal January returns are more pronounced for firms with expected losses that are expected to persist. The findings enhance our understanding of the loss/profit anomaly. Our study also shows that the degree of market inefficiency and abnormal returns documented by prior studies has been significantly understated. Specifically, ignoring this reversal understates the hedge returns one could earn by exploiting the expected loss/profit anomaly by up to 45%—ignoring the January reversal earns an average annual hedge returns of 9.63% compared to 17.39% when the January reversal is incorporated.

Second, the paper contributes to the literature on the determinants of the return predictability of expected earnings and other accounting performance metrics. Prior literature has

[17] Fundamental value is the present value of expected future payoffs (Frankel and Lee 1998; Lee et al. 1999; Lee 2001).

[18] The literature's interest in how investors value loss firms is in part driven by the increasing number of firms reporting accounting losses in different markets (Klein and Marquardt 2006; Balkrishna, at al. 2007; Wu, et al. 2010; Jiang and Stark 2013).

largely focused on cross-sectional determinants of the return predictability of accounting performance variables. Mashruwala and Mashruwala (2011) is the only paper that examines the effect of calendar time on the relation between an accounting measure—Accruals Quality—and stock returns.[19] Since AQ reflects the second moment (i.e., standard deviation of residuals), their study does not provide direct evidence on the valuation of the level variables such as expected earnings. This paper documents the importance of the calendar-time dimension by showing that the positive return predictability of expected earnings reverses the sign to negative in January. Researchers ignoring this effect can observe lower or even opposite return predictability, depending on which months dominate the study sample. Our study also contributes to the literature on market efficiency with respect to accounting information. In this literature, finding higher (lower) future risk-adjusted returns is usually interpreted as evidence of under(over)valuation due to investor under-(over-) weighting of the accounting information. Our findings show that this is not always the case: overvalued firms with expected losses earn higher future returns in January.[20]

Finally, our paper contributes to the January effect literature. Previous research has mainly focused on the January effect for small stocks. In this paper, we argue that tax-loss selling behavior that drives the January effect should be especially important for stocks with poor accounting performance such as those with expected losses. Consistent with this argument, we show that expected losses explain a significant part of the abnormal January returns. In fact, expected losses

[19] Several papers examine variations in mispricing and autocorrelation of earnings across fiscal quarters due to the integral approach to interim reporting and find lower mispricing after fourth-quarter earnings announcements (Bernard and Thomas 1989, 1990; Rangan and Sloan 1998; Narayanamoorthy 2006). These studies are different from ours because they examine the effect of fiscal quarter rather than calendar time and because, for most firms, fourth-quarter earnings are announced after January.

[20] To our knowledge, ours is the first paper that empirically shows that under(over)valued firms can systematically earn lower (higher) future risk-adjusted returns.

are a better predictor of the abnormal January returns than are most variables examined by prior studies.

The remainder of the paper is organized as follows. In the next section, we discuss the data and research design. Section 3 presents the empirical results. Section 4 summarizes and concludes.

2. Data and methodology

2.1 Sample selection

Our sample consists of NYSE/AMEX/Nasdaq firms available in I/B/E/S, CRSP, and Compustat. Analyst earnings forecasts are obtained from I/B/E/S. Stock prices and returns are from CRSP. Book values of equity, earnings, and other accounting information are obtained from Compustat. In all our tests, to ensure that accounting information is available to investors, we use the most recently available fiscal year that ended four months prior to the portfolio formation date. We consider only securities identified as ordinary common shares (CRSP share codes 10 and 11) and exclude firms with stock prices below one dollar at the portfolio formation date. Our final sample includes 1.193 million firm-month observations over the period from June 1982 through December 2011.

2.2 Portfolio construction and time-series tests

Each month, we form two portfolios based on that month's analyst consensus annual earnings forecast: firms with negative forecasts (the expected loss (EL) portfolio) and firms with non-negative forecasts (the expected profit (EP) portfolio).[21] Annual earnings forecasts are for the nearest fiscal year for which earnings have not yet been announced. To calculate the return

[21] In our robustness analysis, we show that the results are robust to using different measures of expected losses/profits and different times of when expected losses/profits are measured.

performance of the EL and EP portfolios relative to each other, we form the EPEL hedge portfolio, which buys stocks in the EP portfolio and short sells stocks in the EL portfolio. We then track the portfolios' returns over the next month. To compute the average abnormal return, we estimate the four-factor time-series model (Fama and French 1993; Carhart 1997). Specifically, we estimate the following regression:

$$RET_{pt} - RF_t = \alpha_p + \beta_{1p}(MKT_t - RF_t) + \beta_{2p}SMB_t + \beta_{3p}HML_t + \beta_{4p}UMD_t + \varepsilon_{pt}, \qquad (1)$$

where RET_p is the monthly portfolio return; *RF* is the risk-free rate (one-month Treasury bill rate); *MKT* is the return on the market portfolio measured as the CRSP value-weighted return; and *SMB*, *HML*, and *UMD* are returns on the size, book-to-market, and momentum factors in month *t*. The intercept, α_p, is the portfolio average monthly abnormal return. We estimate the four-factor model separately for all months, non-January months, and January.

2.3 Cross-sectional tests and additional control variables

In addition to the time-series portfolio tests, we employ Fama and MacBeth (1973) cross-sectional regressions to control for several firm characteristics associated with January returns. Specifically, we estimate the following regression:

$$RET_t = a + b_1 EPROFIT_{t-1} + \gamma\ CONTROLS_{t-1} + \varepsilon_t, \qquad (2)$$

where RET_t is the future one-month stock return, *EPROFIT* is an indicator variable that equals one (zero) for firms with expected profits (losses),[22] and *CONTROLS* is a vector of control variables that are associated with January returns: firm size, *SIZE*; CAPM beta, *BETA* (Tinic and West

[22] Defined in such a way, the coefficient on *EPROFIT* represents the return earned by the hedge portfolio that buys (sells) expected profit (loss). In other words, the coefficient on *EPROFIT* is the return on the EPEL hedge portfolio described in the previous section.

1984); book-to-market ratio, *BM* (Davis 1994; Loughran 1997); momentum, *MOM* (Jegadeesh and Titman 1993; Liu, et al. 1999); stock price, *PRICE* (Bhardwaj and Brooks 1992); return volatility, *RET.VOL* (Doran et al. 2014); and accruals quality, *AQ* (Mashruwala and Mashruwala 2011). The definitions of all other variables are provided in the appendix.

We rank all control variables into deciles and scale them such that they range from zero to one. In addition to mitigating the influence of extreme observations, this allows us to interpret regression coefficients as returns for hedge portfolios that buy (sell) stocks with high (low) values of the relevant control variable. Furthermore, this allows us to compare the economic effect of the expected losses/profits, with that of control variables by comparing the magnitudes of their respective hedge returns. We estimate cross-sectional regression (2) each month and report time-series averages of estimated coefficients. The statistical significance is based on Fama-MacBeth *t*-statistics with the Newey-West adjustment for autocorrelation (Fama and MacBeth 1973; Newey and West 1987).[23]

3. Empirical analyses

3.1 Descriptive statistics

Table 1, Panel A reports descriptive statistics for our sample. The 0.86 mean of the *EPROFIT* variable indicates that 86% (14%) of our firm-month observations have expected profits (losses). Additional analysis shows that expected losses have become more widespread over time: the average percentage of firms with expected losses has increased from 8.4% in the first half of the sample period to 18.5% in the second half (untabulated). As in other studies that use I/B/E/S

[23] Consistent with standard practice for Newey-West estimation, we use a lag length equal to the smallest integer greater than $T^{0.25}$ (Greene 2003, 267), which in our case equals 3. Lag lengths of 1, 2, and 4 yield substantially similar results.

analyst forecasts, firms in our sample are relatively large, with a mean (median) market capitalization of $1,804 ($280) million. On average, 43% of shares are owned by institutional investors (*IO* mean is 0.43).

Panel B of Table 1 shows means and medians for the subsamples of EP firms (columns one and two) and EL firms (columns three and four), along with their differences (columns five and six). EP firms tend to be less risky, as indicated by lower CAPM betas and higher market capitalization (differences in means are -0.581 and 1489, respectively). As expected, EP firms on average have higher past stock returns (the difference in means for *MOM* is 20.6%). They also have higher institutional ownership and lower *AQ* (higher accruals quality) with difference in means of 0.066 and -0.050, respectively. Correlations between *EPROFIT* and other variables presented in Panel C are consistent with these observations.

3.2 January reversal in the relation between expected losses/profits and future returns

Before formally testing the predicted January reversal in the expected loss/profit drift, we present descriptive evidence on our prediction. Specifically, we report future returns earned by firms with expected losses (EL portfolio) and firms with expected profits (EP portfolio), and the difference in future returns between the two groups (EPEL portfolio) for each calendar month (Table 2). The portfolios are formed based on the I/B/E/S consensus annual earnings forecast in the month prior to the month of return calculation. The statistical significance is based on Fama-MacBeth *t*-statistics with the Newey-West adjustment for autocorrelation. The returns reported in Table 2 provide first evidence on the January reversal in the relation between expected losses/profits and future returns. The average monthly EPEL return difference is a positive 1.22% in non-January months. The return difference is positive in all eleven non-January months. In contrast, in January the EPEL return difference is a *negative* 3.88%. In other words, stocks with expected losses earn significantly higher January returns than stocks with expected profits. Incorporating the reversal significantly enhance hedge returns earned by the EPEL trading strategy: the sum of EPEL hedge returns for all months ignoring the January reversal is 9.63% while the sum of EPEL hedge returns for all months incorporating the January reversal is 17.39%, an 81% increase in the total annual hedge return.

Figure 1 shows graphically the market-adjusted returns earned by EL and EP portfolios from July of year *t* to June of year *t+1* for each sample year *t*. For each portfolio, the plot depicts returns earned by the strategy that buys stocks in that portfolio and short sells the equally weighted portfolio of NYSE/AMEX/Nasdaq firms available in I/B/E/S, CRSP, and Compustat. Consistent with the results in Table 2, there is a noticeable downward (upward) price drift for EL (EP) firms throughout most of the year, and a large price movement in the opposite direction in January. It takes around four months to undo the January reversal. [24]

To check the consistency of the January reversal across years, we plot non-January EPEL hedge returns (Figure 2, Panel A) and January EPEL hedge returns (Figure 2, Panel B) for each sample year. The plot shows that non-January EPEL returns are positive in most of the sample years (22 out of 29 years). In contrast, January EPEL returns are negative in the majority of the sample years (23 out of 29 years). The binomial test rejects the null that positive and negative returns are equally likely (the two-tailed *p*-value is 0.0023 (0.0081) for January (non-January) months). Additional analysis shows that the January EPEL returns are negative and significant in each of the sample decades—the 1980s, 1990s, and 2000s—with the 1990s having the most negative January EPEL hedge returns (untabulated).

[24] A similar return drift and January reversal is observed when we plot buy-and-hold returns for portfolios that are formed once a year in June and then held constant for the following twelve months (untabulated).

Table 3 documents the consistency of the January reversal across different types of stocks. In addition to showing the influence of firm characteristics on the relation between expected losses/profits and future returns, partitioning on firm characteristics also controls for the variable used in the partition. The results in Panel A show that the January (non-January) EPEL returns are negative (positive) in all size groups, statistically significant for small and medium firms, and greater in magnitude for small firms than for large firms. Panels B and C show the results for subsamples based on book-to-market ratio and past returns, respectively. The January EPEL returns are negative and significant for growth, neutral, and value stocks as well as for stocks with low, medium, and high past returns. The non-January EPEL returns are positive and significant for all of these types of stocks except for those with high past returns. Furthermore, in all three Panels, both EL and EP firms have higher raw returns in January than in non-January months and the January increase is notably larger for EL firms than for EP firms. The finding is consistent with the argument that both EL and EP firms have a positive probability of tax-loss selling while tax-loss selling is more likely for EL firms.

Table 4 presents the results of our first formal test of the January reversal. The test uses the four-factor time series model (equation 1) to test the significance of risk-adjusted returns for the EPEL portfolio. The table presents results for the samples consisting of all months (Panel A), non-January months (Panel B), and January (Panel C). For non-January (all months), the average abnormal EPEL hedge return is positive and significant, 1.0% (0.7%) per month, *t*-stat = 4.47 (2.68). In contrast, in January the abnormal EPEL hedge return is negative and significant (-2.5% per month, *t*-stat = -2.59).[25]

[25] As a robustness check, we also estimate the risk-adjusted returns using the Fama-French (2015) five-factor model that adds profitability and investment factors to the Fama-French (1993) three-factor model (for details, see Fama and

Overall, the results in Tables 2, 3, and 4 and in Figure 2 are consistent with the predicted January reversal. The positive expected loss/profit drift in non-January months reverses to a negative one in January. This behavior is robust across sample years and different types of stocks and is not explained by the four-factor asset pricing model.

3.3 Evidence from international markets

Tests employing data from international markets are often used to provide largely independent out-of-sample evidence on stock market behavior (Setiono and Strong 1998; Pincus et al. 2007; Soares and Stark 2009; Novy-Marx 2013). To examine whether the reverse January relation holds outside of the United States, we use firms in developed market countries that have taxes on capital gains and a December tax year-end.[26] The required financial data are obtained from Compustat Global and I/B/E/S. The abnormal returns are calculated using Fama and French (2012) global factors.[27] The sample spans from June 1992 through December 2011. Table 5 reports the results of the test of abnormal returns of the EPEL hedge portfolio. Consistent with the US findings in Table 4, the EPEL portfolio earns positive abnormal returns in non-January months (1.2%, *t*-stat = 2.48) and negative abnormal returns in January (-7.5%, *t*-stat = -4.30).

Further, the results in Table 5 show that ignoring the reverse January relation can lead to erroneous conclusions about stock price efficiency. The abnormal return for the entire calendar year is indistinguishable from zero (0.7%, t-stat=1.24), which incorrectly suggests that there is no relation between expected losses/profits and future abnormal returns.

French 2015). Consistent with the results in Table 4, we find the abnormal EPEL hedge returns are positive in non-January months (0.63% per month, t-stat = 3.74) and negative in January (-2.37% per month, t-stat = -3.24) (untabulated).

[26] Specifically, the sample includes the following countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, and Switzerland.

[27] We are grateful to Kenneth French for providing the data on his website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

3.4 Expected losses/profits vis-à-vis other predictors of January return

To estimate and compare the incremental economic effect of expected losses/profits with that of other predictors of January returns, we use cross-sectional regressions. Table 6 reports the results of monthly Fama-MacBeth (1973) cross-sectional regressions of stock returns on the expected losses/profits variable, *EPROFIT*, and control variables (equation 2). First, without any controls (columns 1, 4, and 7), the results show that expected losses (profits) are associated with lower (higher) future returns in the full and non-January sample (the EPEL return spread is 0.8% and 1.2%, respectively) but higher (lower) future returns in January (the EPEL return spread is -3.9%). Controlling for the four risk factors—beta, size, book-to-market, and momentum (columns 2, 4, and 8) reduces the EPEL return spread to 0.5% (*t*-stat = 2.39), 0.8% (*t*-stat = 3.53), and -2.4% (*t*-stat = -2.90) for all months, non-January months, and January, respectively. Finally, when all control variables are included (columns 3, 5, and 9), the incremental EPEL return spread is 0.4% (*t*-stat = 1.96), 0.6% (*t*-stat = 3.02), and -1.7% (*t*-stat = -2.67) for all months, non-January months, and January, respectively. The regression results reveal the following. First, the factors used as control variables explain about half of the January EPEL return spread ((0.039-0.017)/0.039=56%). Second and most importantly, the effect of *EPROFIT* is different from all other predictors of January returns, since *EPROFIT* is the only variable for which the return predictability reverses from one significant relation in non-January months to the opposite significant relation in January.[28] Third, the incremental January spread for EPEL is greater in magnitude than that for *SIZE*, *BETA*, *BM*, *MOM*, and *AQ*, and lower than that for *PRICE*.

[28] In the univariate regression, the return predictability of momentum also reverses from significantly positive in non-January months to significantly negative in January (untabulated). However, the momentum January effect is subsumed by other variables, including *EPROFIT*.

Therefore, the economic effect of *EPROFIT* is greater than that of the majority of the variables examined by the prior literature.

Overall, although controlling for various firm characteristics explains a significant portion of the reverse January relation, the incremental effect of expected losses/profits remains significant and stronger than the effect of most other variables.

3.5 Robustness tests

We perform several robustness tests to check the sensitivity of the January reversal to alternative ways of how and when earnings expectations are measured. In our first test, instead of using earnings forecasts in the month prior to the portfolio formation date we use forecasts in a fixed calendar month. Specifically, we fix a calendar month between March and December.[29] We then measure *EPROFIT* in that month and use it in the Fama-MacBeth regressions over the following twelve calendar months. This alternative design allows us to check the robustness of our results to using different time of when earnings expectation is measured. Furthermore, fixing the calendar month in which earnings forecast is measured allows us to rule out the possibility that the results are driven by the differences in earnings forecasts measured in different calendar months. Similar to Table 6, the results show that, for all measurement months from March to December, the coefficient on *EPROFIT* reverses from a significant positive one in the regression of non-January returns to a significant negative one in the regression of January returns. For example, when *EPROFIT* is measured in June and all control variables are included in the regression, the

[29] We start in March since for a typical December fiscal year-end firm annual earnings are announced before the date on which the March consensus forecast is issued.

monthly EPEL spread is 0.5% (t-stat=2.51) in the non-January return regression and -3.2% (t-stat = -4.66) in the January return regression (untabulated).[30]

In our second test, we use a continuous measure of expected earnings instead of the expected loss/profit indicator. Specifically, we scale expected earnings by total assets where total assets are measured at the end of the most recent fiscal year for which the data are available. Similar to other variables, we rank the measure into deciles and scale it to range from 0 to 1. Similar to Table 6, the results show that the coefficient on expected earnings is significantly positive in non-January months and significantly negative in January. When all control variables are included, the monthly return spread between the top and bottom decile is 1.0% (t-stat=3.14) in non-January months and -3.2% (t-stat=-2.86) in January (untabulated).

Finally, we use *realized* losses/profits for the most recent fiscal year for which the data are available. Since past earnings represent expected earnings under a random walk model the test allows us to check the robustness of our results to using earnings expectations that are not based on analyst forecasts. The results for the cross-sectional regressions show that the coefficient on *EPROFIT* based on realized losses/profits is significantly positive in non-January months and significantly negative in January. When all control variables are included, the monthly return spread is 0.5% (t-stat=2.57%) in non-January months and -3.6% (t-stat=-3.84) in January (untabulated). We also repeat the test using realized earnings scaled by total assets instead of an indicator variable

[30] The results of the four-factor asset pricing tests are qualitatively similar. For example, when *EPROFIT* is measured in June, the monthly abnormal EPEL return is 0.7% (t-stat=3.01) in the non-January return regression and -4.7% (t-stat = -4.97) in the January return regression.

Across different specifications, the results of our main and robustness tests are often significant even when using more conservative test statistic critical values suggested by Harvey, et al. (2016),[31] which provides further evidence of the robustness of our results.

3.6 Reverse January relation and tax-loss selling

We next test the prediction that the reverse January relation is caused by tax-loss selling by individual investors. Our test approach follows Mashruwala and Mashruwala (2011). We use two proxies for the likelihood of tax-loss selling (*TLS*). The first proxy, *PTLS* (probability of tax-loss selling), equals the negative of the ratio of the stock price at the end of year (excluding the last five trading days) and the maximum stock price over the year (excluding the last five trading days) (Reinganum 1983; Chang and Pinegar 1986; Mashruwala and Mashruwala 2011). A greater (i.e. less negative) value of *PTLS* corresponds to a greater price decline from the recent maximum price and therefore a higher likelihood of a short-term capital loss, which in turn corresponds to a higher probability of tax-loss selling. The second tax-loss selling proxy, *ARET*, equals the negative of the buy-and-hold return over the previous calendar year (excluding last five trading days) (Sias and Starks 1997; Poterba and Weisbenner 2001; Mashruwala and Mashruwala 2011). Similar to *PTLS*, a higher value of *ARET* (i.e. more negative returns) corresponds to a higher likelihood of capital losses and tax-loss selling.

We estimate the following Fama and MacBeth (1973) cross-sectional regression of January returns:

$$\begin{aligned} January\ RET_t = a + b_1 EPROFIT_{t-1} + b_2 TLS_{t-1} + b_3 EPROFIT_{t-1} * TLS_{t-1} \\ + CONTROLS_{t-1} + \varepsilon_t \end{aligned} \tag{3}$$

[31] Harvey et al. (2016) recommend a much higher hurdle, such as a t-statistic greater than 3.0, for current research to document a new asset pricing factor.

where *TLS* is a proxy for the likelihood of tax-loss selling, i.e. *PTLS* or *ARET*. We expect that the relation between expected losses/profits and January returns to be more negative when the likelihood of tax-loss selling is high, i.e. we expect the coefficient b_3 on *EPROFIT*TLS* to be negative and significant. The significance of the signed prediction for b_3 is based on a one-tailed test.

Further, since tax-loss selling incentives are expected to be stronger for individual investors, we examine whether the relation between tax-loss selling and the reverse January relation is more pronounced when institutional ownership, *IO*, is low. Specifically, we rank *IO* across all firms at the end of every December and assign observations below (above) the median into the Low (High) *IO* group. *IO* is calculated as the sum of all institutional holdings of the stock at the end of December scaled by the number of shares outstanding. We then estimate equation (3) within the Low and High *IO* subsamples, respectively.

The test results are reported in Table 7. For the entire sample, the coefficient on *EPROFIT*TLS* is negative and significant when using *PTLS* (-0.038, t = -2.19, column 1) and *ARET* (-0.020, t = -1.70 (p = 0.045), column 3) as tax-loss selling proxies, consistent with the reverse January relation being stronger when the likelihood of tax-loss selling is higher. The subsample results show that the effect of tax-loss selling on the reverse January relation is only observed for firms with low institutional ownership (columns 2 and 4) and is insignificant for firms with high institutional ownership (columns 3 and 6). The result provides further evidence consistent with the tax-loss selling explanation since tax-loss selling incentives are expected to be higher for individual investors (low institutional ownership).

Overall, the empirical evidence from tests employing both tax-loss selling proxies and institutional ownership is consistent with the prediction that the reverse January relation is at least partly caused by tax-loss selling.

3.7 Information hypothesis and window dressing

As an alternative to tax-loss selling explanation, we examine whether the information hypothesis or window-dressing by institutional investors explain the reverse January relation.

According to the information hypothesis, December fiscal year-end firms and firms with earnings announcements in January have greater information uncertainty and risk due to the expected release of financial information. Therefore, these firms are expected to earn higher January returns to compensate for their higher risk. Thus to test the information hypothesis, we use the following two proxies of greater uncertainty due to expected information releases: an indicator variable equal to one for December fiscal year-end firms and zero otherwise; and an indicator variable equal to one for firms with earnings announcements in January and zero otherwise.

According to the window-dressing hypothesis, portfolio managers sell loser stocks and buy winner stocks at the end of the year to make their portfolios look better for fund investors. We calculate a proxy for the probability of window dressing by institutional investors (*PWD*) as the decrease in institutional ownership if the stock is a loser and the increase in institutional ownership if the stock is a winner. Specifically, if the stock return over the 12-month period ending in month *t-1* is negative (positive), then *PWD* equals the negative of the change in *IO* from the end of

September to the end of December. Greater values of *PWD* reflect greater net selling of loser stocks or greater net buying of winner stocks by institutional investors prior to the calendar year-end.[32]

To test the information and window dressing hypotheses, we estimate the following Fama and MacBeth (1973) cross-sectional regressions of January returns:

$$January\ RET_t = a + b_1 EPROFIT_{t-1} + b_2 EPROFIT_{t-1}{*}X_{t-1} + b_3 X_{t-1} + CONTROLS_{t-1} + \varepsilon_t \qquad (4)$$

where X is either one of the three proxies for the information hypothesis or the probability of window dressing (*PWD*). If the information hypothesis (window dressing) explains the reverse January relation, we expect the coefficient b_2 on the interactions of *EPROFIT* and the proxies for the information hypothesis (window dressing) to be negative and significant. The significance of the signed prediction for b_2 is based on a one-tailed test.

The results are reported in Table 8. Both the interaction between *EPROFIT* and the indicator of December fiscal year-end (0.004, t = 0.55, column 1) and the interaction between *EPROFIT* and the indicator of January earnings announcement (0.007, t = 1.14, column 2) are insignificant. The findings are not consistent with the information hypothesis explaining the reverse January relation.[33] The result in the last column show that the window dressing is also unlikely to explain the reverse January relation. The coefficient on *EPROFIT*PWD* is insignificant (0.001, t = 0.21, column 3).

[32] Our proxy is crude since it is based on the quarterly institutional ownership data. Ideally, a window-dressing proxy would be based on daily stock transactions by specific institutions. Similarly, an ideal tax-loss selling proxy would be based on daily stock transactions by specific individuals. Since we do not have access to such data, our tests of the window-dressing and tax-loss selling hypotheses may have low power.

[33] Also, with respect to returns around earnings announcements, Chambers and Penman (1984) find that unexpectedly early (late) earnings reports tend to bring good (bad) news as indicated by announcement window returns. If January returns are caused by EL (EP) firms with January earnings announcements that contain good (bad) news, we should expect the reverse January relation to be stronger when earnings are announced in January. The results in Table 8 column 2 suggest that January earnings announcements are unlikely to explain our findings.

Overall, the evidence in Tables 7 and 8 is consistent with the prediction that the reverse January relation is at least partly caused by tax-loss selling. In contrast, we do not find that the information hypothesis or window dressing by institutional investors explain the reverse January relation.

3.8 The role of low expected earnings and expected losses

Our study is motivated by the idea that tax-loss selling should be especially important for pricing firms with poor accounting performance such as those with expected negative earnings. In addition to expected losses, positive but low expected earnings can also indicate poor financial performance and therefore should be also be affected by tax-loss selling. Based on this argument, we expect that the reverse January relation should be largely driven by firms with expected losses and firms with low positive expected earnings. To examine the validity of this prediction, we plot future January returns against the expected earnings level, where the expected earnings level is annual earnings forecast scaled by total assets.[34] The resulting return predictability function shown in Figure 3 is consistent with the above prediction. The reverse January relation is strongly concentrated among stocks with low expected earnings (i.e. when expected earnings are negative or close to zero). Stocks with expected losses earn especially large January returns. In contrast, there is little relationship between the expected earnings level and January returns when expected earnings are high.

[34] The graph is constructed in the following way. For each percentile X of the distribution of the expected earnings level, we form a portfolio of stocks with expected earnings between X-3% and X+3%, where X ranges from 3% to 97%. We then plot the mean portfolio return against the level of expected earnings corresponding to the Xth percentile. Using decile ranks of the expected earnings level results in a less detailed but qualitatively similar return predictability function.

3.9 The reverse January relation and likelihood of loss reversal

The link between expected losses and tax-loss selling is likely to depend on the type of losses. If losses are expected to reverse in the near future they are less likely to result in capital losses and tax-loss selling behavior as compared to losses that are expected to persist. In this section, we examine whether the reverse January relation is affected by the likelihood of loss reversal.

To proxy for the likelihood of loss reversal, we use the following variables associated with higher probability of loss reversal (Joos and Plesko 2005). Return on assets (*ROA*); market value of equity (*SIZE*); an indicator variable equal to one if the current year's earnings is negative and the prior year's earnings is positive, and zero otherwise (*FIRSTLOSS*); the negative of the number of sequential losses in the past five years before the current loss (*LOSS_SEQ*)[35]; an indicator variable equal to one if the firm pays dividends and zero otherwise (*DIVDUM*); and the negative of the indicator variable that equals one if the firm stops paying dividends in the current year and zero otherwise (*DIVSTOP*).[36] Similar to Joos and Plesko (2005), we also estimate the probability of reversal, *PLR,* based on the logistic model that includes all individual predictors of loss reversal.

To test for the effect of the likelihood of loss reversal, we estimate the following Fama and MacBeth (1973) cross-sectional regression of January returns:

$$\begin{aligned} January\ RET_t = a + b_1 EPROFIT_{t-1} + b_2 EPROFIT_{t-1} * LR_{t-1} + b_3 LR_{t-1} \\ + CONTROLS_{t-1} + \varepsilon_t \end{aligned} \quad (5)$$

[35] Joos and Plesko (2005) argue that firms have a higher probability of moving from losses to profitability when losses are less severe (i.e. less negative or higher ROA), when firms are larger and hence financially stronger, when the loss is the first in a sequence, when the loss sequence is shorter, when firms pay dividends, and a lower probability of moving from losses to profitability when firms stop paying dividends in the current year. Two loss reversal predictors in Joos and Plesko (2005)—*LOSS_SEQ* and *DIVSTOP*—have negative association with the probability of loss reversal. We multiply these two variables by minus one in order to allow for a uniform interpretation of the sign for all loss reversal proxies.

[36] In addition to these six variables, the main model of loss reversal in Joos and Plesko (2005) also includes past return on assets and sales growth but these two variables have insignificant association with the probability of loss reversal, so we omit them here.

where *LR* is a proxy for the likelihood of loss reversal (i.e. *ROA*, *SIZE*, *FIRSTLOSS*, *LOSS_SEQ*, *DIVDUM*, *DIVSTOP*, or *PLR*). We expect that the relation between expected losses/profits and January returns to be less negative when losses are temporary, i.e., we expect the coefficient b_2 on *EPROFIT*LR* to be positive and significant. The significance of the signed prediction for b_2 is based on a one-tailed test.

The test results reported in Table 9 are consistent with the predicted negative relation between the reverse January relation and the likelihood of loss reversal. The interaction between *EPROFIT* and *LR* is positive for all seven proxies of the likelihood of loss reversal and significant for all proxies except *DIVSTOP*. The findings are consistent with the capital gains and tax-loss selling being less likely when expected losses are likely to reverse.[37]

3.10 Effect on stock under(over)valuation

Predictable abnormal future returns are typically associated with preexisting mispricing and future stock price correction. Specifically, higher (lower) future risk-adjusted returns are usually interpreted as the correction of prior under(over)valuation. To examine the effect of the reverse January relation on stock mispricing, we use two proxies of firms' relative under(over)valuation.

First, we use predictable stock returns around future earnings announcements as an ex post proxy of mispricing (Bernard and Thomas 1990; Sloan 1996; Piotroski 2000). If EL (EP) firms are under(over)valued in December and their high (low) January returns represent a price correction, then we would also expect returns around future earnings announcements to be high (low). If,

[37] In an additional analysis, we follow Joos and Plesko (2005) and examine how investors price the R&D component of expected earnings. The untabulated results show that investors value R&D expense positively in both non-January and January months. In contrast, the coefficient on expected earnings before R&D expense reverses from positive in non-January months to negative in January months suggesting that the results are robust to excluding R&D expense. We also find that R&D expense is positively correlated with the tax-loss selling proxies, *PTLS* and *ARET*, indicating that even though R&D expense itself is positively valued by investors, the types of firms that have high R&D are more likely to have high tax-loss selling.

however, EL (EP) firms are over(under)valued in December and their subsequent high (low) returns in January represent a *price drift away from fundamental value*, then we would expect returns around future earnings announcements to be low (high). The results in Table 10 Panel A are consistent with the latter. The EPEL hedge portfolio formed in December earns positive returns around future earnings announcements (1.81% total hedge return and 0.59%, 0.40%, 0.53%, and 0.29% hedge returns for quarters q+1 to q+4, respectively). So, despite their higher (lower) January returns, EL (EP) firms actually appear to be relatively over(under)valued. Further, consistent with the negative January EPEL returns mainly driven by firms with expected losses, the positive EPEL hedge returns around future announcements are also mainly driven by EL firms. Therefore, it appears that the higher returns earned by EL firms in January are followed by greater return reversals around future earnings announcements.

Second, to corroborate the above finding based on ex post stock returns, we also use firms' fundamental-value-to-price ratios as an ex ante proxy of mispricing (Frankel and Lee 1998; Lee, et al. 1999). We calculate value-to-price, *V/P*, ratios following the methodology in Lee et al. (1999). The results in Table 10 Panel B show that EL firms have significantly lower mean and median *V/P* ratios than EP firms. The significant difference in value-to-price ratios is consistent with the finding in Panel A that EL (EP) firms are relatively over(under)valued.

Panel C combines the ex ante and ex post proxies of under(over)valuation by calculating returns around future earnings announcements for high and low V/P groups within EP and EL portfolios. We rank all EP firms in a given December based on their V/P ratios and assign firms above (below) the median into the High and Low V/P groups. We repeat the process for EL firms. The results indicate that EPEL returns are concentrated among low V/P firms (total EPEL returns are 1.82% and 0.85% for low and high V/P, respectively). In particular, the EPEL returns are mainly driven by low returns for EL firms with low V/P (total market-adjusted return of -1.36%), consistent with these stocks being most overvalued.[38] Also, the results show that the difference in returns around future earnings announcements between High and Low V/P firms tends to be positive (total return difference of 0.11% and 1.07% for EP and EL firms in the bottom row),[39] which is consistent with these firms' relatively high and low ex ante valuation, respectively.

Overall, predictable returns around future announcements suggest that EL (EP) firms are relatively over(under)valued and so high (low) returns earned by these firms in January do not correct the mispricing but rather exacerbate it. The greater mispricing is then corrected by return reversals around future earnings announcements.

4. Conclusion

This paper examines the role of January in the relation between expected losses/profits and future stock returns. We find that the expected loss/profit drift reverses to a negative one in January. Returns earned by the expected loss/profit drift are significantly enhanced when the reverse January relation is incorporated into the trading strategy. The reverse January relation is economically large, is observed in the United States as wells as international markets, and is incremental to other variables associated with January returns. The reverse January relation is at least partly caused by tax-loss selling by individual investors. Additional analysis shows that the reverse January relation leads to an abnormal price *drift away from fundamental value*.

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[38] Although there are significant differences between V/P and BM since book value of equity does not capture the present value of future cash flows (earnings), there is also a significant overlap between V/P and BM. The Pearson (Spearman) correlation between the two variables is 0.20 (0.33) (Table 1 Panel C). When we use BM instead of V/P, the result in Table 10 Panel C continues to hold. However when we use V/P instead of BM, the result in Table 3 Panel B is flipped (January EPEL is more (less) negative for firms with low (high) V/P (-4.17% for low VP and -3.78% for high VP, untabulated). The finding confirms that there are significant differences between low V/P and low BM firms.
[39] Except for EL firms in q+1, the return differences between High and Low V/P groups are not statistically significant (untabulated).

Collectively, our findings suggest that tax-loss selling is an important source of the mispricing of firms with expected losses/profits. The positive relation between expected losses/profit and future abnormal returns documented in prior research is significantly negative in January. It appears that stock prices, instead of converging toward the fundamental value that reflects expected losses/profits, temporarily move in the opposite direction. Therefore, stock prices become less efficient in January. This finding is inconsistent with the general view that stock prices become more efficient over time and that positive (negative) future risk-adjusted returns indicate under(over)valuation. Overall, the paper illustrates the importance of controlling for the effect of January when examining the pricing of firms with expected losses/profits.

Appendix: Variable Definitions

Variable		Definition
AQ	=	The accruals quality measure developed by Dechow and Dichev (2002), as modified by McNichols (2002). *AQ* is estimated from a regression of total current accruals on lagged, current, and future cash flows, plus the change in revenue and the current level of property, plant, and equipment. The regression is estimated each year for each of Fama and French's (1997) 48 industry groups with at least 20 observations. *AQ* is the standard deviation of the firm's residuals over the previous five years.
ARET	=	Proxy for the probability of tax-loss selling, measured as the negative of the buy-and-hold return over the previous calendar year (excluding last five trading days) (Sias and Starks 1997; Poterba and Weisbenner 2001; Mashruwala and Mashruwala 2011).
BETA	=	The firm's CAPM beta, estimated from a regression of firm returns minus the risk-free (one-month T-bill) rate on the value-weighted market index minus the risk-free rate over the 60-month period ending in month *t-1*.
BM	=	The book-to-market ratio, calculated as the book value of equity divided by the market value of equity at the end of the most recent fiscal year for which the data are available.
DIVDUM	=	Indicator variable that equals one if the firm pays a dividend in the current year.
DIVSTOP	=	The indicator variable that equals one if the firm stops paying dividends in the current year, and zero otherwise; the measure is multiplied by negative one.
EPROFIT	=	Indicator variable that equals one if the I/B/E/S consensus annual earnings forecast in month *t-1* is non-negative, and zero otherwise.
FIRSTLOSS	=	Indicator variable that equals one if the current year's earnings is negative and the prior year's earnings is positive, and zero otherwise.
IO	=	Institutional ownership, measured as the sum of all institutional holdings of the stock scaled by the number of shares outstanding. The measure is based on the most recent institutional ownership data available in month *t-1*.
LOSS_SEQ	=	The number of sequential losses over the past five years before the current loss; the measure is multiplied by negative one.
MOM	=	Stock return momentum measured as the firm's stock return over the period *t-12* to *t-2* (Grinblatt and Moskowitz 2004; Asness et al. 2013; Novy-Marx 2013).
PLR	=	The probability of loss reversal, estimated from a logistic regression of the loss reversal indicator on *ROA*, *SIZE*, *FIRSTLOSS*, *LOSS_SEQ*, *DIVDUM*, and *DIVSTOP*. The regression is estimated each year and annual estimated coefficients from the prior year are applied to the current year variables to compute the probability of loss reversal.
PRICE	=	Stock price at the end of month *t-1* (excluding last five trading days).
PTLS	=	Proxy for the probability of tax-loss selling, measured as the negative of the ratio of the stock price at the end of the previous calendar year (excluding the last five trading days) and the maximum stock price over the year (excluding the last five trading days) (Sias and Starks 1997; Poterba and Weisbenner 2001; Mashruwala and Mashruwala 2011).

PWD	=	Proxy for the probability of window dressing by institutional investors at the end of the calendar year. The proxy equals the decrease (increase) in *IO* from September 31 to December 31 if the stock return over the 12-month period ending in month *t-1* is negative (positive).
RET	=	Future one-month stock return measured after the portfolio formation month *t-1*.
RET.VOL	=	Return volatility, measured as standard deviation of the daily return over the 12-month period ending in month *t-1*.
ROA	=	Return on asset, measured as the income before extraordinary items divided by total assets; the measure is ranked into deciles, across all firm in a given December, and scaled to range from 0 to 1.
SIZE	=	Firm size, measured as the market capitalization (in millions) at the end of month *t-1*. The variable is ranked, across all firm in a given month, into deciles and scaled to range from 0 to 1.
TLS	=	Tax-loss selling proxy, either *PTLS* or *ARET*, defined below.
V/P	=	Value-to-price ratio, calculated as the intrinsic value of equity divided by the market value of equity. The intrinsic value of equity is calculated following the methodology in Lee, et al. (1999).

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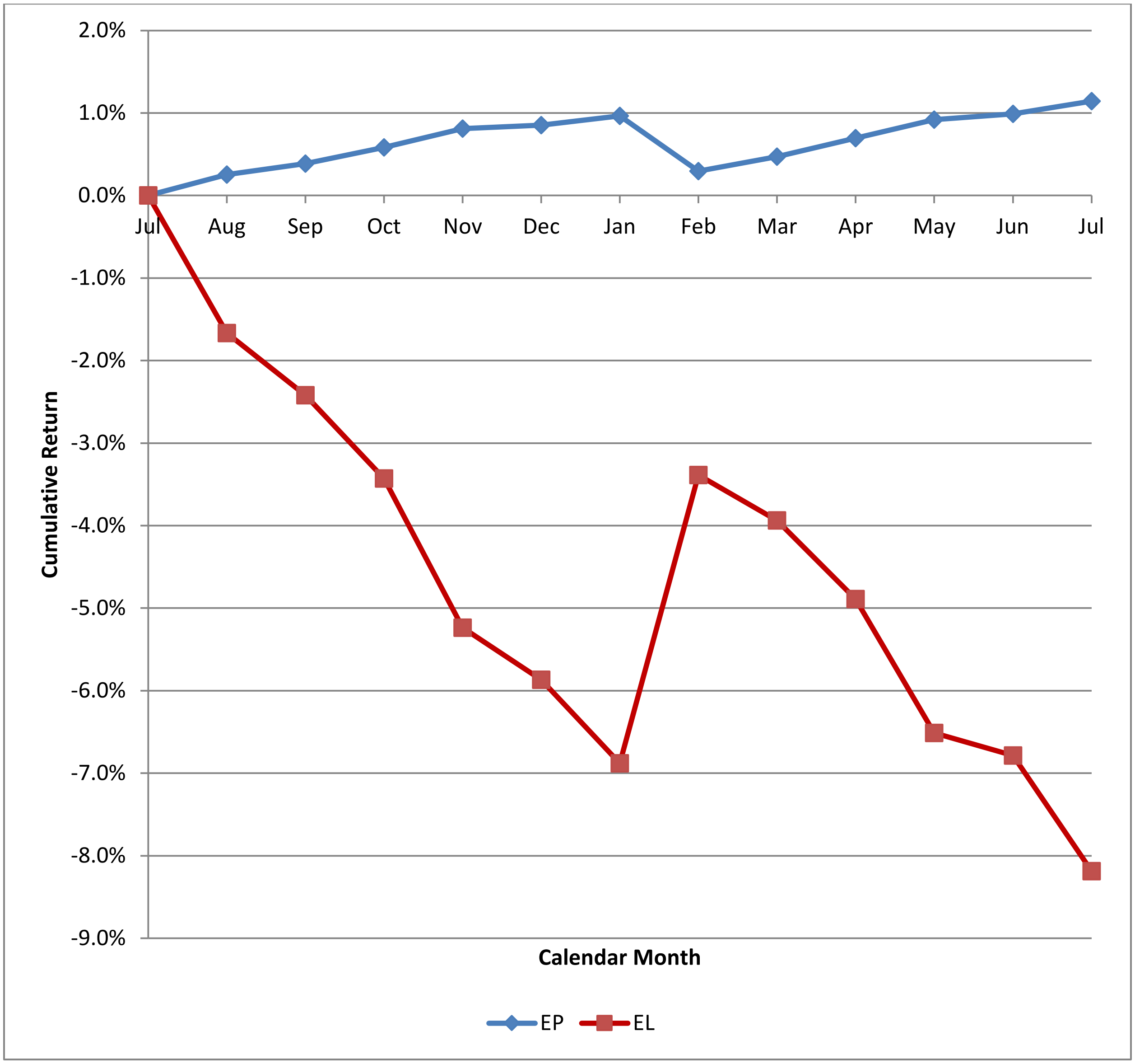
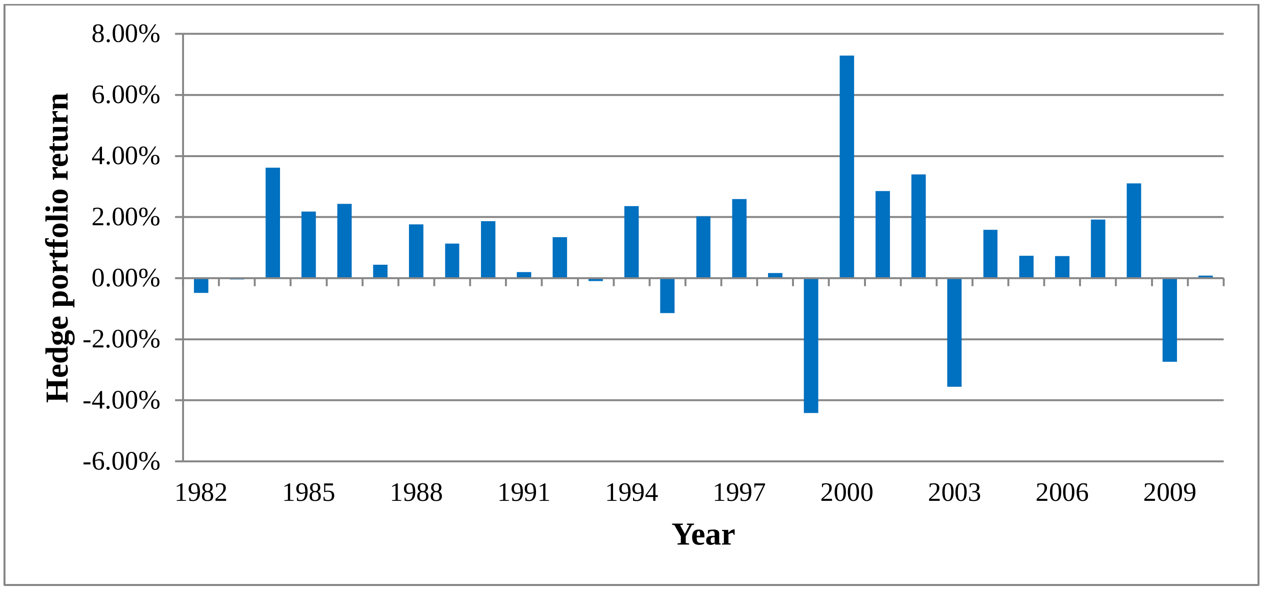
Figure 1: Cumulative market-adjusted returns for stocks with expected profits (EP) and expected losses (EL)



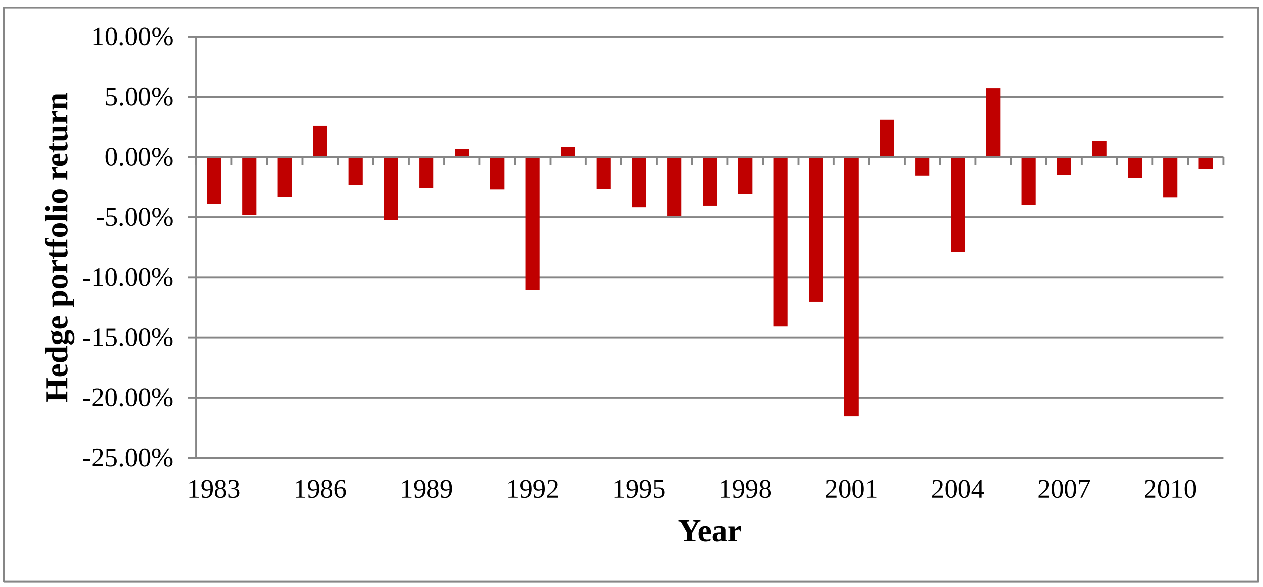
This figure shows cumulative market-adjusted returns for portfolios of stocks with expected profits, EP (diamonds) and expected losses, EL (squares). For each portfolio, the plot depicts returns earned by the strategy that buys stocks in that portfolio and short sells the equally weighted portfolio of NYSE/AMEX/Nasdaq firms available in I/B/E/S, CRSP, and Compustat. The returns are cumulated from July of year *t* to June of year *t+1*, *t* =1982-2010. The returns are then averaged across sample years. Stocks are assigned to the EP (EL) portfolio each month if the analysts' consensus forecast in that month is non-negative (negative).

Figure 2: EPEL hedge returns by year

Panel A Non-January months



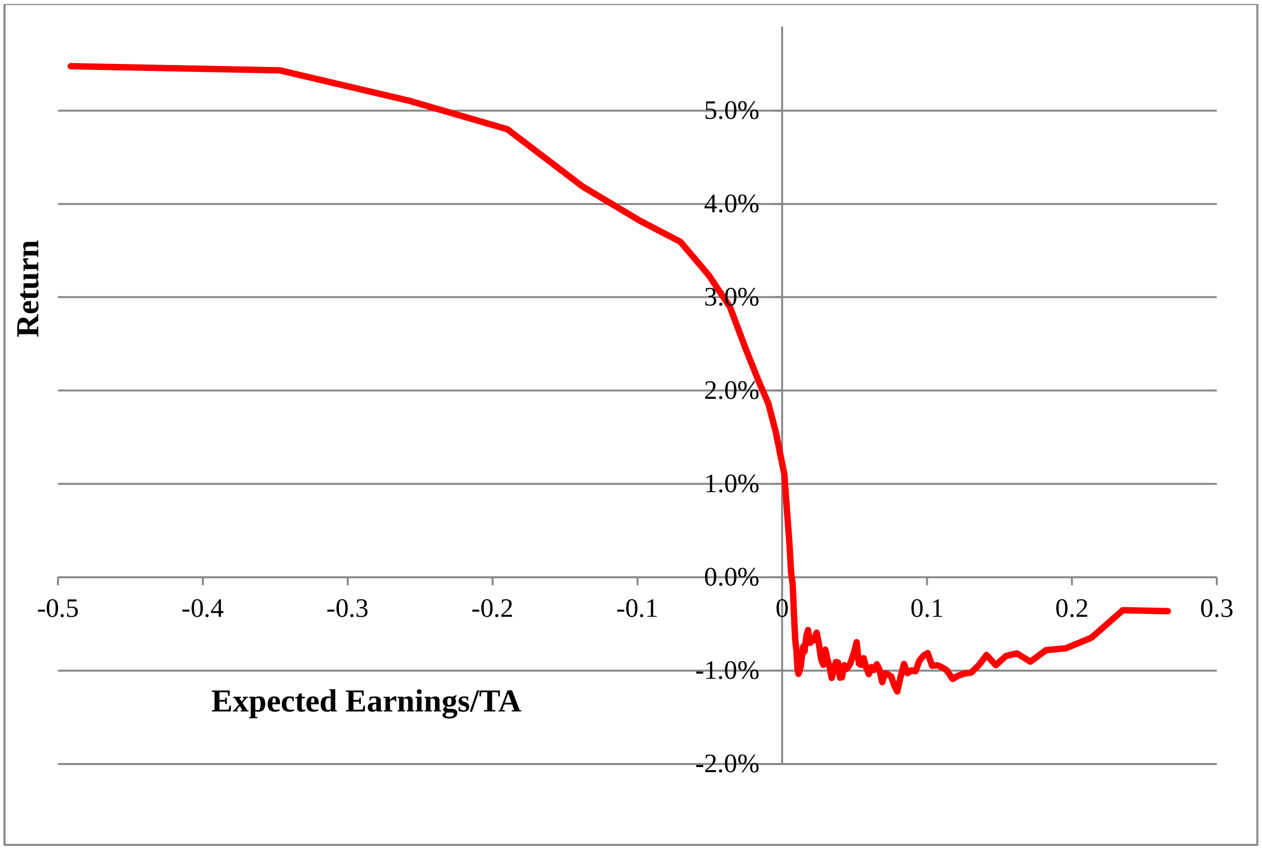
Panel B January



This figure presents average monthly returns by calendar year to the EPEL hedge portfolio. The EPEL hedge portfolio takes a long position in stocks with a non-negative analyst consensus earnings forecast (the EP portfolio) and a short position in stocks with a negative analyst consensus earnings forecast (the EL portfolio). The equally weighted hedge return is then calculated over the subsequent month. Panel A (Panel B) reports non-January (January) EPEL hedge returns. The sample period is from June 1982 through December 2011.

Figure 3: The reverse January return predictability function

January returns against earnings forecast



This figure plots future market-adjusted January returns against the level of expected earnings in December of the prior year. Market-adjusted returns are calculated relative to the portfolio of NYSE/AMEX/Nasdaq firms available in I/B/E/S, CRSP, and Compustat. Expected earnings is analysts' annual earnings forecast scaled by total assets. Total assets are measured at the end of the most recent fiscal year for which the data are available. The graph is constructed in the following way. For each percentile X of the distribution of expected earnings, we form a portfolio of stocks with expected earnings between X-3% and X+3%, where X ranges from 3% to 97%. We then plot the mean portfolio return against the level of expected earnings corresponding to the X^{th} percentile.

Table 1: Descriptive statistics

Panel A: Descriptive statistics for the full sample

Variable	Mean	Std. Dev.	Q1	Median	Q3
RET	0.010	0.157	-0.063	0.005	0.075
EPROFIT	0.860	0.653	1.000	1.000	1.000
SIZE	1804	5180	88	280	1039
BETA	1.157	0.753	0.641	1.052	1.529
BM	0.704	0.567	0.336	0.583	0.919
MOM	0.147	0.538	-0.179	0.075	0.354
PRICE	21.765	17.525	8.770	17.250	29.500
RET.VOL	0.032	0.017	0.020	0.028	0.040
AQ	0.075	0.087	0.025	0.046	0.087
IO	0.425	0.270	0.198	0.391	0.627
PTLS	-0.743	0.213	-0.921	-0.796	-0.605
ARET	-0.160	0.569	-0.377	-0.081	0.186
PWD	0.006	0.080	-0.023	0.004	0.036
ROA	0.005	0.163	0.004	0.034	0.075
FIRSTLOSS	0.076	0.265	0	0	0
LOSS_SEQ	0.839	1.349	0	0	1
DIVDUM	0.440	0.496	0	0	1
DIVSTOP	0.026	0.158	0	0	0
PLR	0.784	0.182	0.718	0.834	0.912
V/P	0.783	0.657	0.373	0.689	1.095

Panel B: Means and medians for expected profit (EP) and expected loss (EL) subsamples

	EL		EP		Difference	
Variable	Mean	Median	Mean	Median	Mean	Median
RET	0.004	-0.014	0.012	0.007	**0.008**	**0.021**
SIZE	523	128	2012	328	**1489**	**201**
BETA	1.663	1.538	1.081	1.000	**-0.581**	**-0.538**
BM	0.675	0.440	0.709	0.598	**0.033**	**0.158**
MOM	-0.032	-0.206	0.175	0.102	**0.206**	**0.307**
PRICE	9.739	6.000	23.715	19.375	**13.976**	**13.375**
RET.VOL	0.050	0.047	0.029	0.026	**-0.021**	**-0.021**
AQ	0.118	0.081	0.068	0.042	**-0.050**	**-0.039**
IO	0.368	0.313	0.434	0.405	**0.066**	**0.092**
PTLS	-0.587	-0.594	-0.768	-0.820	**-0.181**	**-0.225**
ARET	0.026	0.213	-0.189	-0.110	**-0.215**	**-0.323**
PWD	0.008	0.004	-0.189	-0.110	**-0.197**	**-0.113**
ROA	-0.225	-0.131	0.042	0.043	**0.268**	**0.174**
FIRSTLOSS	0.162	0	0.06233	0	**-0.099**	**0**
LOSS_SEQ	2.334	2	0.59591	0	**-1.738**	**-2**
DIVDUM	0.108	0	0.4944	0	**0.387**	**0**
DIVSTOP	0.038	0	0.02369	0	**-0.014**	**0**
PLR	0.581	0.623	0.818	0.853	**0.237**	**0.230**
V/P	0.146	0.074	0.872	0.748	**0.725**	**0.674**

Panel C: Pearson (bottom) and Spearman (top) correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	*EPROFIT*		**0.19**	**-0.23**	**0.10**	**0.20**	**0.37**	**-0.39**	**-0.23**	**0.09**	**-0.26**	**-0.20**	**-0.01**	**0.38**
(2)	*SIZE*	**0.19**		**-0.03**	**-0.24**	**0.22**	**0.72**	**-0.43**	**-0.18**	**0.58**	**-0.26**	**-0.23**	**-0.02**	**-0.02**
(3)	*BETA*	**-0.26**	**-0.03**		**-0.14**	**-0.07**	**-0.21**	**0.38**	**0.28**	**0.10**	**0.23**	**0.08**	**0.03**	**-0.59**
(4)	*BM*	**0.01**	**-0.24**	**-0.09**		**-0.25**	**-0.20**	**-0.11**	**-0.26**	**-0.06**	**0.08**	**0.37**	0.00	**0.33**
(5)	*MOM*	**0.11**	**0.15**	**0.03**	**-0.24**		**0.41**	**-0.24**	**-0.08**	**-0.02**	**-0.58**	**-0.95**	**0.08**	**-0.09**
(6)	*PRICE*	**0.27**	**0.68**	**-0.17**	**-0.21**	**0.27**		**-0.61**	**-0.32**	**0.36**	**-0.47**	**-0.42**	**-0.02**	**0.09**
(7)	*RET.VOL*	**-0.44**	**-0.39**	**0.37**	**0.01**	**-0.06**	**-0.44**		**0.44**	**-0.17**	**0.49**	**0.24**	**0.02**	**-0.27**
(8)	*AQ*	**-0.19**	**-0.08**	**0.21**	**-0.14**	**0.01**	**-0.17**	**0.25**		**0.03**	**0.21**	**0.08**	**0.03**	**-0.25**
(9)	*IO*	**0.08**	**0.55**	**0.08**	**-0.05**	**-0.05**	**0.34**	**-0.16**	**0.04**		**-0.05**	**0.02**	0.00	**-0.01**
(10)	*PTLS*	**-0.30**	**-0.25**	**0.25**	**0.14**	**-0.41**	**-0.40**	**0.53**	**0.13**	**-0.04**		**0.64**	**-0.01**	**-0.16**
(11)	*ARET*	**-0.13**	**-0.04**	**-0.01**	**0.34**	**-0.96**	**-0.29**	**0.09**	**-0.01**	**0.05**	**0.51**		**-0.07**	**0.07**
(12)	*PWD*	**-0.01**	**-0.02**	**0.03**	**0.02**	**0.06**	**-0.03**	**0.03**	**0.02**	**-0.01**	**0.03**	**-0.06**		**-0.01**
(13)	*V/P*	**0.37**	**-0.02**	**-0.49**	**0.20**	**-0.12**	**0.03**	**-0.20**	**-0.14**	**0.00**	**-0.13**	**0.10**	**-0.01**	

This table reports descriptive statistics for the main variables of interest. Panel A reports the descriptive statistics for the full sample. Panel B shows means and medians separately for the subsample of firms with expected profits (EP) and the subsample of firms with expected losses (EL). The last two columns show the difference in means and medians between EP and EL subsamples. Differences significant at the five percent level are marked in bold (all differences are significant at the five percent level). Panel C reports the correlation matrix (Pearson correlations are shown below the main diagonal, and Spearman correlations are shown above). Correlations significant at the five percent level are marked in bold (all correlations in the table are significant at the five percent level). All variables are defined in the appendix. The sample period is from June 1982 through December 2011.

Table 2: Monthly market-adjusted returns for EP and EL portfolios

Month	EP	EL	EPEL
January	**-0.61%**	**3.27%**	**-3.88%**
	(-2.46)	**(3.52)**	**(-3.33)**
February	0.18%	-0.55%	0.73%
	(0.99)	(-0.91)	(0.94)
March	0.22%	-0.95%	1.18%
	(1.44)	(-1.48)	(1.49)
April	0.22%	**-1.62%**	1.85%
	(1.11)	**(-2.00)**	(1.85)
May	0.07%	-0.27%	0.35%
	(0.60)	(-0.46)	(0.49)
June	0.15%	**-1.40%**	**1.55%**
	(1.39)	**(-2.46)**	**(2.35)**
July	0.25%	**-1.67%**	**1.92%**
	(1.68)	**(-3.37)**	**(3.04)**
August	0.13%	-0.75%	0.89%
	(1.65)	(-1.77)	(1.80)
September	0.19%	-1.01%	1.21%
	(1.24)	(-1.56)	(1.54)
October	0.23%	**-1.81%**	**2.04%**
	(1.80)	**(-2.76)**	**(2.69)**
November	0.04%	-0.63%	0.67%
	(0.22)	(-0.70)	(0.62)
December	0.11%	-1.01%	1.12%
	(1.03)	(-1.73)	(1.65)
All Months	0.10%	**-0.71%**	**0.81%**
(n = 354 months)	(1.33)	**(-2.21)**	**(2.07)**
Non-January Months	**0.16%**	**-1.06%**	**1.22%**
(n = 325 months)	**(2.23)**	**(-3.59)**	**(3.37)**

The table reports equally weighted market-adjusted returns by calendar month for firms with expected profits (EP portfolio), firms with expected losses (EL portfolio), and the difference in returns between the two groups (EPEL portfolio) for each calendar month. The portfolios are based on the I/B/E/S consensus annual earnings forecast in the month prior to the month of return calculation. Market-adjusted returns are calculated relative to the portfolio of NYSE/AMEX/Nasdaq firms available in I/B/E/S, CRSP, and Compustat. The Newey-West autocorrelation adjusted *t*-statistics are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1982 through December 2011.

Table 3: Returns for subsamples based on size, book-to-market, and momentum

Panel A: Returns for subsamples based on size

	All months (n = 354 months)			Non-January months (n = 325 months)			January (n = 29 months)		
	Small	Medium	Large	Small	Medium	Large	Small	Medium	Large
EP	1.24%	1.26%	1.14%	0.94%	1.22%	1.14%	4.58%	1.77%	1.13%
EL	0.38%	0.46%	0.75%	-0.35%	0.15%	0.55%	8.67%	3.92%	2.97%
EPEL	**0.86%**	**0.80%**	0.39%	**1.29%**	**1.07%**	0.59%	**-4.09%**	**-2.15%**	-1.84%
t-stat	**(2.68)**	**(2.30)**	(1.06)	**(3.69)**	**(2.86)**	(1.58)	**(-2.97)**	**(-2.25)**	(-1.47)

Panel B: Returns for subsamples based on book-to-market

	All months (n = 354 months)			Non-January months (n = 325 months)			January (n = 29 months)		
	Low (Growth)	Medium (Neutral)	High (Value)	Low (Growth)	Medium (Neutral)	High (Value)	Low (Growth)	Medium (Neutral)	High (Value)
EP	1.07%	1.16%	1.41%	1.01%	1.10%	1.23%	1.66%	1.92%	3.46%
EL	0.23%	0.28%	0.66%	-0.20%	-0.19%	0.01%	5.07%	5.47%	7.91%
EPEL	**0.83%**	**0.89%**	**0.75%**	**1.21%**	**1.28%**	**1.22%**	**-3.41%**	**-3.55%**	**-4.46%**
t-stat	**(2.67)**	**(2.38)**	**(2.33)**	**(3.72)**	**(3.14)**	**(3.31)**	**(-3.43)**	**(-2.59)**	**(-2.80)**

Panel C: Returns for subsamples based on momentum

	All months (n = 354 months)			Non-January months (n = 325 months)			January (n = 29 months)		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
EP	0.84%	1.21%	1.56%	-0.61%	1.15%	1.53%	3.51%	1.90%	1.87%
EL	0.03%	0.62%	1.51%	-1.22%	0.28%	1.17%	7.28%	4.47%	5.33%
EPEL	**0.81%**	0.59%	0.05%	**1.15%**	**0.87%**	0.36%	**-3.78%**	**-2.57%**	**-3.46%**
t-stat	**(2.67)**	(1.69)	(0.14)	**(4.02)**	**(2.46)**	(1.10)	**(-3.00)**	**(-2.16)**	**(-4.00)**

The table reports returns for subsamples based on size (*SIZE*), book-to-market (*BM*), and momentum (*MOM*). Each month stocks are sorted into three equally sized groups based on the level of *SIZE* (in Panel A), *BM* (in Panel B), and *MOM* (in Panel C). Within each group, the table reports equally weighted returns for firms with expected profits (EP portfolio), firms with expected losses (EL portfolio), and the difference in returns between the two groups (EPEL hedge portfolio) for each calendar month. The portfolios are based on the I/B/E/S consensus annual earnings forecast in the month prior to the month of return calculation. The returns are reported for all sample months (first three columns), non-January months (the middle three columns), and January (the last three columns). The Newey-West autocorrelation adjusted *t*-statistics are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1982 through December 2011. All variables are defined in the appendix.

Table 4: Test of abnormal returns for EPEL hedge portfolio using the four-factor model

Panel A: All months (n = 354 months)

	Intercept	R_m-R_f	*SMB*	*HML*	*UMD*	Adj. R^2
EPEL	**0.007**	**-0.233**	**-0.768**	**0.500**	**0.303**	0.55
t-stat	**(2.68)**	**(-4.76)**	**(-8.01)**	**(3.92)**	**(4.09)**	

Panel B: Non-January months (n = 325)

	Intercept	R_m-R_f	*SMB*	*HML*	*UMD*	Adj. R^2
EPEL	**0.010**	**-0.242**	**-0.722**	**0.526**	**0.267**	0.57
t-stat	**(4.47)**	**(-4.59)**	**(-7.70)**	**(4.05)**	**(3.34)**	

Panel C: January (n = 29)

	Intercept	R_m-R_f	*SMB*	*HML*	*UMD*	Adj. R^2
EPEL	**-0.025**	-0.194	**-0.816**	0.277	**0.350**	0.43
t-stat	**(-2.59)**	(-1.38)	**(-3.04)**	(0.96)	**(2.93)**	

This table reports results of a test of the abnormal returns of the EPEL hedge portfolio using the four-factor time-series model (Fama and French 1993; Carhart 1997). The intercept is the portfolio average monthly abnormal return. R_m-R_f, *SMB*, *HML*, and *UMD* are returns on the market, size, book-to-market, and momentum factors. Other variables are defined in the appendix. Results are presented for all months (Panel A), non-January months (Panel B), and January (Panel C). The Newey-West autocorrelation adjusted *t*-statistics are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1982 through December 2011.

Table 5: Abnormal returns for international sample

Panel A: All months (n = 222 months)

	Intercept	R_m-R_f	*SMB*	*HML*	*UMD*	Adj. R^2
EPEL	0.007	-0.167	**-0.454**	**0.997**	**0.281**	0.070
t-stat	(1.24)	(-1.93)	**(-2.42)**	**(4.54)**	**(2.22)**	

Panel B: Non-January months (n = 204)

	Intercept	R_m-R_f	*SMB*	*HML*	*UMD*	Adj. R^2
EPEL	**0.012**	-0.154	-0.219	**0.969**	**0.266**	0.062
t-stat	**(2.48)**	(-1.70)	(-1.51)	**(4.66)**	**(2.09)**	

Panel C: January (n = 18)

	Intercept	R_m-R_f	*SMB*	*HML*	*UMD*	Adj. R^2
EPEL	**-0.075**	**-0.400**	0.105	**2.476**	-0.250	0.350
t-stat	**(-4.30)**	**(-2.95)**	(0.24)	**(3.15)**	(-0.82)	

This table reports results of a test of the abnormal returns of the EPEL hedge portfolio for the sample of countries that have taxes on capital gains and a December tax year-end, excluding the United States. The sample includes the following countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, and Switzerland. The abnormal returns are tested using the Fama and French (2012) global factors. Intercept is the portfolio average monthly abnormal return. R_m-R_f, *SMB*, *HML*, and *UMD* are returns on the market, size, book-to-market, and momentum global factors. Other variables are defined in the appendix. Results are presented for all months (Panel A), non-January months (Panel B), and January (Panel C). The Newey-West autocorrelation adjusted *t*-statistics are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1992 through December 2011.

Table 6: Fama-MacBeth cross-sectional regressions

$$RET_t = a + b_1\ EPROFIT_{t-1} + b_2\ SIZE_{t-1} + b_3\ BETA_{t-1} + b_4\ BM_{t-1} + b_5\ MOM_{t-1} + b_6\ PRICE_{t-1} + b_7\ RET.VOL_{t-1} + b_8\ AQ_{t-1} + \varepsilon_t$$

	All months (n=354 months)			Non-January months (n = 325 months)			January (n = 29 months)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.004	-0.004	0.004	-0.013	-0.010	0.000	**0.063**	0.054	0.043
	(0.71)	(-0.84)	(0.59)	(-0.22)	(-1.79)	(-0.02)	**(3.58)**	(3.19)	(3.62)
EPROFIT	**0.008**	**0.005**	**0.004**	**0.012**	**0.008**	**0.006**	**-0.039**	**-0.024**	**-0.017**
	(2.41)	**(2.39)**	**(1.96)**	**(3.36)**	**(3.53)**	**(3.02)**	**(-3.27)**	**(-2.90)**	**(-2.67)**
SIZE		-0.004	**-0.004**		0.000	-0.003		**-0.046**	-0.013
		(-1.40)	**(-1.96)**		(0.16)	(-1.44)		**(-3.05)**	(-1.42)
BETA		-0.003	0.002		0.000	0.001		**0.028**	**0.013**
		(0.89)	(0.86)		(0.10)	(0.33)		**(2.85)**	**(2.31)**
BM		**0.008**	**0.007**		**0.007**	**0.006**		**0.017**	**0.013**
		(3.26)	**(3.47)**		**(3.09)**	**(3.34)**		**(3.02)**	**(2.33)**
MOM		**0.015**	**0.013**		**0.018**	**0.015**		-0.008	-0.005
		(5.84)	**(5.13)**		**(5.93)**	**(5.23)**		(-0.85)	(-0.63)
PRICE			-0.003			-0.001			**-0.031**
			(-1.25)			(-0.21)			**(-3.02)**
RET.VOL			-0.004			-0.006			0.021
			(-1.02)			(-1.55)			(1.84)
AQ			-0.001			-0.001			0.006
			(-0.89)			(-1.51)			(1.79)
Adj. R^2	0.013	0.049	0.057	0.013	0.048	0.055	0.016	0.065	0.076

This table presents the time-series mean coefficients from monthly cross-sectional regressions of stock returns on *EPROFIT* and control variables. Results are reported for all months (Columns 1–3), non-January months (Columns 4–6), and January months (Columns 7–9). All independent variables except *EPROFIT* are ranked into deciles and scaled to range from 0 to 1. Fama-MacBeth *t*-statistics with the Newey-West adjustment for autocorrelation are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1982 through December 2011. All variables are defined in the appendix.

Table 7: Tax-loss selling and the role of institutional ownership

$$\text{January } RET_t = a + b_1 EPROFIT_{t-1} + b_2 TLS_{t-1} + b_3 EPROFIT_{t-1} * TLS_{t-1} + b_4\, SIZE_{t-1} + b_5\, BETA_{t-1} + b_7\, BM_{t-1} + b_8\, MOM_{t-1} + b_9\, PRICE_{t-1} + b_{10}\, RET.VOL_{t-1} + b_{11}\, AQ_{t-1} + \varepsilon_t$$

	Tax-loss Selling Proxy (TLS) (n = 29 months)					
	PTLS			***ARET***		
	(1) All Obs.	(2) IO=Low	(3) IO=High	(4) All Obs.	(5) IO=Low	(6) IO=High
Intercept	0.030	0.036	0.015	0.028	0.035	0.010
	(2.72)	(3.72)	(1.15)	(3.10)	(4.60)	(0.94)
EPROFIT	-0.028	-0.039	-0.015	-0.022	-0.029	-0.014
	(-2.86)	(-3.18)	(-1.57)	(-2.37)	(-2.62)	(-1.49)
TLS	0.011	0.004	0.016	0.095	0.099	0.086
	(2.21)	(0.87)	(2.68)	(7.09)	(6.95)	(5.18)
*EPROFIT*TLS*	**-0.038**	**-0.061**	-0.014	**-0.020**	**-0.027**	-0.011
	(-2.19)	**(-2.80)**	(-0.62)	**(-1.70)**	**(-2.03)**	(-0.63)
SIZE	-0.014	-0.022	-0.003	-0.014	-0.021	-0.004
	(-1.51)	(-2.00)	(-0.33)	(-1.62)	(-2.23)	(-0.37)
BETA	0.011	0.011	0.015	0.015	0.013	0.018
	(2.18)	(1.75)	(2.69)	(2.57)	(2.22)	(3.02)
BM	0.014	0.018	0.017	0.010	0.013	0.015
	(2.37)	(4.11)	(2.34)	(1.63)	(2.96)	(1.96)
MOM	0.001	-0.003	0.003	0.082	0.085	0.074
	(0.14)	(-0.43)	(0.45)	(9.71)	(6.65)	(7.30)
PRICE	-0.028	-0.045	-0.016	-0.025	-0.039	-0.013
	(-2.88)	(-4.14)	(-1.79)	(-2.48)	(-3.58)	(-1.51)
RET.VOL	0.159	0.020	0.012	0.022	0.025	0.019
	(1.56)	(1.83)	(1.28)	(1.90)	(1.97)	(1.72)
AQ	0.006	0.005	0.004	0.005	0.005	0.003
	(1.78)	(1.29)	(1.06)	(1.69)	(1.27)	(0.88)
Adj. R^2	0.080	0.076	0.084	0.084	0.080	0.889

This table presents the time-series mean coefficients from monthly cross-sectional regressions of January stock returns on *EPROFIT*TLS* and control variables, where *TLS* is one of the two tax-selling proxies: *PTLS* (columns 1-3) and *ARET* (columns 4-6). All independent variables except *EPROFIT* are ranked into deciles and scaled to range from 0 to 1. All variables are defined in the appendix. Columns 1 and 4 show the results for the entire sample. Columns 2 and 5 (3 and 6) show the results for the subsamples with Low (High) institutional ownership, *IO*. The subsamples are constructed by ranking *IO* across all firms at the end of every December and assigning observations below (above) the median to the Low (High) *IO* subsample. Fama-MacBeth *t*-statistics with the Newey-West adjustment for autocorrelation are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test, except for the signed predictions for *EPROFIT*TLS*, which are based on a one-tailed test. The sample period is from June 1982 through December 2011. All variables are defined in the appendix.

Table 8: Testing the Information Hypothesis and Window Dressing

$$January\ RET_t = a + b_1 EPROFIT_{t-1} + b_2 EPROFIT_{t-1} * X_{t-1} + b_3 X_{t-1} + CONTROLS_{t-1} + \varepsilon_t$$

	Information Hypothesis Proxies		***Window Dressing Proxy***
	(1) December fiscal year-end (n = 29 months)	(2) January earnings announcement (n = 29 months)	(3) Probability of window dressing (n = 29 months)
Intercept	**0.044**	**0.043**	**0.045**
	(3.53)	**(3.32)**	**(3.84)**
EPROFIT	**-0.021**	**-0.018**	**-0.018**
	(-2.12)	**(-2.50)**	**(-2.47)**
*EPROFIT*X*	0.004	0.007	0.001
	(0.55)	(1.14)	(0.21)
X	-0.004	0.007	-0.001
	(-0.58)	(0.88)	(-0.25)
SIZE	-0.012	-0.016	-0.013
	(-1.34)	(-1.62)	(-1.45)
BETA	**0.013**	**0.012**	**0.013**
	(2.26)	**(2.12)**	**(2.31)**
BM	**0.016**	0.011	**0.013**
	(2.73)	(1.91)	**(2.33)**
MOM	-0.003	-0.004	-0.006
	(-0.36)	(-0.45)	(-0.69)
PRICE	**-0.033**	**-0.035**	**-0.031**
	(-3.10)	**(-3.17)**	**(-2.95)**
RET.VOL	0.021	0.020	0.021
	(1.86)	(1.80)	(1.87)
AQ	0.006	**0.007**	0.006
	(2.01)	**(2.19)**	(1.84)
Adj. R^2	0.080	0.083	0.078

This table presents the time-series mean coefficients from monthly cross-sectional regressions of January stock returns on *EPROFIT*X* and control variables. In the first two columns *X* is one of two information hypothesis proxies: an indicator variable equal to one for December fiscal year-end firms and zero otherwise (column 1); an indicator variable equal to one for firms with January earnings announcements and zero otherwise (column 2). In Column 3, *X* is the probability of window dressing, *PWD*. All independent variables except *EPROFIT* are ranked into deciles and scaled to range from 0 to 1. All variables are defined in the appendix. The regressions are estimated within the specified subsamples. Fama-MacBeth *t*-statistics with the Newey-West adjustment for autocorrelation are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1982 through December 2011.

Table 9: The reverse January relation and the likelihood of loss reversal

$$January\ RET_t = a + b_1 EPROFIT_{t-1} + b_2 EPROFIT_{t-1} * LR_{t-1} + b_3 LR_{t-1} + CONTROLS_{t-1} + \varepsilon_t$$

	Proxy of likelihood for loss reversal (***LR***)						
	(1) *ROA* (n = 29)	(2) *SIZE* (n = 29)	(3) *FIRST LOSS* (n = 29)	(4) *LOSS_ SEQ* (n = 29)	(5) *DIV DUM* (n = 29)	(6) *DIV STOP* (n = 29)	(7) *PLR* (n = 28)
Intercept	**0.062**	**0.071**	**0.046**	0.030	**0.044**	**0.043**	**0.124**
	(4.07)	**(4.65)**	**(3.81)**	(1.86)	**(3.87)**	**(3.58)**	**(3.48)**
EPROFIT	**-0.034**	**-0.054**	**-0.020**	-0.005	**-0.019**	**-0.017**	**-0.058**
	(-3.05)	**(-4.30)**	**(-2.95)**	(-0.68)	**(-2.71)**	**(-2.46)**	**(-2.60)**
*EPROFIT*LR*	**0.003**	**0.008**	**0.015**	**0.002**	**0.018**	0.002	**0.062**
	(3.30)	**(4.44)**	**(2.63)**	**(2.21)**	**(2.21)**	(0.07)	**(2.08)**
LR	**-0.004**	**-0.008**	-0.006	**-0.002**	**-0.015**	-0.003	**-0.136**
	(-3.74)	**(-4.01)**	(-1.00)	**(-2.25)**	**(-1.94)**	(-0.16)	**(-3.58)**
SIZE	-0.013	--	-0.013	-0.013	**-0.013**	-0.013	0.000
	(-1.45)	--	(-1.46)	(-1.42)	**(-1.46)**	(-1.43)	(0.03)
BETA	**0.013**	**0.015**	**0.013**	**0.013**	**0.014**	**0.013**	0.011
	(2.23)	**(2.49)**	**(2.34)**	**(2.20)**	**(2.28)**	**(2.31)**	(1.97)
BM	**0.015**	**0.014**	**0.013**	**0.015**	**0.014**	**0.013**	**0.021**
	(2.85)	**(2.41)**	**(2.30)**	**(2.73)**	**(2.45)**	**(2.32)**	**(4.14)**
MOM	-0.007	-0.003	-0.005	**-0.006**	-0.005	-0.005	0.000
	(-0.86)	(-0.34)	(-0.68)	**(-0.70)**	(-0.62)	(-0.61)	(-0.04)
PRICE	**-0.029**	**-0.033**	**-0.030**	**-0.030**	**-0.031**	**-0.031**	**-0.022**
	(-2.71)	**(-3.31)**	**(-2.91)**	**(-2.76)**	**(-3.06)**	**(-2.99)**	**(-2.12)**
RET.VOL	0.020	**0.022**	0.020	0.020	0.022	0.021	0.015
	(1.78)	**(1.93)**	(1.80)	(1.76)	(1.87)	(1.83)	(1.41)
AQ	0.006	0.006	0.005	0.006	**0.006**	0.006	0.004
	(1.82)	(1.92)	(1.63)	(1.80)	**(1.97)**	(1.77)	(1.44)
Adj. R^2	0.080	0.080	0.078	0.080	0.078	0.077	0.084

This table presents the time-series mean coefficients from monthly cross-sectional regressions of January stock returns on *EPROFIT*LR* and control variables, where *LR* is one of the seven proxies for loss reversal: return on assets (column 1); market value of equity (column 2); an indicator variable equal to one if the was profitable in the prior year, and zero otherwise (column3); the negative of the number of losses in the past five years (column 4); an indicator variable equal to one if the firm pays dividends and zero otherwise (column 5); the negative of the indicator variable that equals one if the firm stops paying dividends in the current year and zero otherwise (column 6); and the probability of loss reversal (column 7). Accounting variables are calculated at the end of the most recently available fiscal year. Fama-MacBeth *t*-statistics with the Newey-West adjustment for autocorrelation are reported in parentheses. Results in bold are significant at the five percent level or lower based on the two-tailed *t*-test, except for the signed predictions for *EPROFIT*LR*, which are based on the one-tailed test. The sample period is from June 1982 through December 2011. All variables are defined in the appendix.

Table 10: Relative under(over)valuation of EP and EL firms

Panel A: Ex-post proxy of under(over)valuation: stock returns around future earnings announcements

Quarter	EP (n = 29)	EL (n = 29)	EPEL (n = 29)	
q+1	0.08%	-0.51%	**0.59%**	**(2.96)**
q+2	0.29%	-0.11%	**0.40%**	**(2.03)**
q+3	0.05%	-0.48%	**0.53%**	**(2.92)**
q+4	-0.05%	-0.34%	0.29%	(1.60)
Total q+1 – q+4	0.37%	-1.44%	**1.81%**	**(2.23)**

Panel B: Ex-ante proxy of under(over) valuation: Value-to-price ratios

	EP (n = 29)		EL (n = 29)		EPEL (n = 29)	
Variable	Mean	Median	Mean	Median	Mean	Median
V/P	0.872	0.748	0.146	0.074	**0.725**	**0.674**
					(20.05)	**(20.71)**

Panel C: Combining ex-ante and ex-post proxies of under(over)valuation

Quarter		EP (n = 29)	EL (n = 29)	EPEL (n = 29)	
q+1	High VP	0.12%	0.06%	0.06%	(0.32)
	Low VP	0.07%	-0.71%	**0.78%**	**(3.29)**
	Diff	0.05%	0.77%		
q+2	High VP	0.40%	0.06%	0.33%	(1.50)
	Low VP	0.25%	-0.13%	0.37%	(1.62)
	Diff	0.15%	0.19%		
q+3	High VP	0.05%	-0.19%	0.24%	(1.20)
	Low VP	0.04%	-0.57%	**0.60%**	**(2.94)**
	Diff	0.01%	0.38%		
q+4	High VP	0.02%	-0.10%	0.12%	(0.55)
	Low VP	0.06%	-0.08%	0.14%	(0.60)
	Diff	-0.04%	-0.02%		
Total q+1 – q+4	High VP	0.57%	-0.29%	0.85%	(1.37)
	Low VP	0.46%	-1.36%	**1.82%**	**(3.49)**
	Diff	0.11%	1.07%		

Panel A reports average daily market-adjusted returns around subsequent earnings announcements. The returns are calculated for expected profit (EP) and expected loss (EL) portfolios and the difference between the two portfolios (EPEL hedge portfolio). The portfolios are formed in December of each sample year based on I/B/E/S consensus annual earnings forecast. The average daily market-adjusted returns are calculated around a 3-day [-1, +1] earnings announcement window for the subsequent four quarterly earnings announcements (rows q+1 to q+4). Market-adjusted returns are measured as raw returns minus the value-weighted market return. Panel B reports mean and median value-to-price ratios, *V/P*, for expected profit firms (EP) and expected loss firms (EL), as well as the difference between EP and EL firms (EPEL). *V/P* ratios are calculated in December of each year following the methodology in Lee, et al. (1999). Panel C reports average daily market-adjusted returns around subsequent earnings announcements for portfolios based on expected profits/losses (EP/EL) and V/P ratios. In a given December, we rank all EP (EL) firms based on their V/P ratios and assign firms above the median into the High V/P group and firms below the median to the Low V/P group. The *t*-statistics are reported in parentheses. Results in bold are significant at the five percent level or lower based on a two-tailed *t*-test. The sample period is from June 1982 through December 2011.