The Information Content of Realized Losses*

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Abstract

A long-standing question in finance asks whether the trades of informed investors predict subsequent stock returns. I argue that a simple conditioning variable should allow us to extract information from the trades of informed investors in a much more efficient way. Specifically, a sale of stock at a loss should be a much more negative signal about future returns than a sale of stock at a gain. I find strong support for this prediction in data on the trades of company insiders, as well as significant additional support in data on the trades of mutual fund managers. I consider a range of explanations for my results, including investor heterogeneity, taxes, the short-swing rule, and rebalancing motives, but find that the evidence is most consistent with the idea that investors derive direct disutility from selling a stock at a loss. Since selling a stock at a loss is painful, an investor who sells at a loss must have particularly negative information, information that manifests itself in a poor stock return over the next few months.

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1 Introduction

A long-standing question in finance asks whether the trades of informed investors (e.g. company insiders) have predictive power for subsequent stock returns. For example, if an insider sells shares in her company’s stock, does the stock perform poorly over the next few months? A large literature suggests that while the purchases of insiders do have predictive power for subsequent returns, the predictive power of sales is surprisingly weak.¹

In this paper, I argue that there is a simple and natural conditioning variable that should allow researchers to extract significantly more information from the trades of informed investors; I then confirm this prediction using data on the trades of company insiders and mutual fund managers. In particular, I argue that a sale by an informed investor at a loss should have much more information content, and much more predictive power for subsequent returns, than a sale by the investor at a gain.

The most direct way to motivate this prediction is through the disposition effect: the robust empirical fact that many groups of investors – even sophisticated investors – have a greater propensity to sell assets at a gain, relative to the reference price, rather than at a loss.² One way of summarizing the disposition effect, a formulation that I make frequent use of, is to say that investors are averse to realizing losses. This aversion has several possible sources, both economic and psychological. For example, it may be due to rebalancing motives: a desire to rebalance their positions means that investors will have a greater propensity to sell assets at a gain rather than at a loss. It may be due to a belief that prices

¹Seyhun (1998) concludes that several different trading rules based on the trades of company insiders lead to profits. Jeng, Metrick, and Zeckhauser (2003) highlight that insider sales do not earn abnormal returns. Lakonishok and Lee (2001) argue that insider selling appears to have no predictive ability.

mean-revert; this would also lead investors to realize gains more frequently than losses. Or it may be due to “realization utility”, in other words, to a direct preference for realizing gains and for not realizing losses.

Whatever the source of the aversion to realizing losses inherent in the disposition effect, the effect naturally leads to the prediction I outlined above. If, for whatever reason, informed investors do not like realizing losses, then seeing them realize a loss – in other words, seeing them sell a stock at a loss – suggests that they must have especially negative information about the future returns of the stock, information that is so negative that it leads them to override their inclination to not realize losses. Put differently, a sale of stock by an informed investor at a loss should be a more negative signal about the returns of the stock over the next few months than a sale of stock at a gain.\(^3\)

To test my prediction, I need to define “realized gain” and “realized loss”. Presumably, an investor views a sale of stock as a realized gain if the current price at which she sells exceeds some reference price she has in mind. In my analysis, I consider a number of natural reference prices, most of them suggested by the prior literature. Most obviously, I use the price at which the stock was purchased – for example, the most recent purchase price, or a weighted-average across all purchase prices. I also conduct tests using a time-series average of recent month-end prices as the reference price.

With this definition of realized gain/loss in hand, I test my prediction using data from the SEC on the trades of company insiders. Specifically, I run a pooled OLS regression of a stock’s future one-month return on two dummy variables: one that indicates if a company insider sold shares of the stock at a loss in the previous month, and another that indicates if a company insider sold shares of the stock at a gain in the previous month. My hypothesis is that the coefficient on the realized loss dummy will be significantly more negative than the coefficient on the realized gain dummy. Importantly, I control for variables that are likely correlated with the dummy variables and that are known to predict returns, such as the stock return.

\(^3\)An implicit assumption underlying my prediction is that the market underreacts to the information in insider trades. Lakonishok and Lee (2001) suggest that this is the case.
over the past year and the capital gains overhang. I also control for other standard predictors of returns such as the book-to-market ratio and market capitalization.

In my results, I find strong support for my prediction. When I take the reference price to be a time-series average of recent prices, the coefficient on the realized loss dummy is -0.59, while the coefficient on the realized gain dummy is -0.01; the difference is statistically significant at the one-percent level with an F-statistic of 25.39. The economic magnitude is significant; a sale below this reference price predicts a return 59 basis points lower than all other firm-months in my sample, while a sale above the moving-average reference price predicts a return only 1 basis point lower. When I take the reference price to be the most recent purchase price, I find an even larger difference in the predictive power of realized gains and realized losses: the coefficient on the realized loss dummy is -0.72, while the coefficient on the realized gain dummy is -0.09; the difference is statistically significant at the one-percent level with an F-statistic of 11.56. Consistent with the hypothesis outlined above, I also find that, if, for a particular company, there is more than one insider sale of stock at a loss in a given month, then this is a more negative signal for future returns than if there is just one sale at a loss. Additionally, if an insider realizes a large loss in the previous month, this is also an especially negative signal.

The predictive power of realized losses allows for the construction of portfolio strategies that, at least before transaction costs, earn high alphas. A value-weighted portfolio that buys stocks that have recently been purchased by insiders and sells stocks that have recently been sold at a loss by insiders (using the most recent purchase price as the reference price) earns four-factor alphas of 108 basis points per month. By contrast, a value-weighted portfolio that buys stocks recently bought by insiders and sells stocks recently sold at a gain by insiders earns alphas of just 42 basis points per month. In short, stocks perform poorly after a sale by an insider at a loss; they do not perform particularly poorly after a sale by an insider at a gain.

Having confirmed my basic prediction, I then try to understand, at a deeper level, what is driving the result. My maintained hypothesis is the one described
earlier: given the aversion to realizing losses that is inherent in the disposition effect, a sale of stock by an insider at a loss should be particularly informative. The investor must have a particularly negative signal about future returns if she is willing to sell despite her typical aversion to doing so.

I first rule out some alternative explanations for my result. For example, one alternative is that company insiders differ in the sophistication of their trading. Under this view, more sophisticated insiders make trades that are more informative about future returns; but they also exhibit the disposition effect less, because they know it to be a mistake. In a pooled OLS regression, we would then observe that sales at a loss would be more informative about future returns than sales at a gain, but this would not be driven by any aversion to realizing losses. To test this view, I run regressions with individual-level fixed effects. Even after doing this, however, I find that sales at a loss have more predictive power for future returns than sales at a gain. This casts doubt on the insider heterogeneity explanation of my result.

If, as the evidence suggests, my result is instead driven by an aversion to realizing losses inherent in the disposition effect, I can still ask: what exactly is driving insiders’ aversion to realizing losses – an aversion that makes their sales at a loss particularly informative? One possibility is a rebalancing motive. If investors like to keep the value of their company stock holdings at a relatively constant fraction of their total wealth, then they will be keen to sell stock after a rise in its value and to not sell after a fall in its value. As a result, a sale at a loss will be particularly informative: the investor must have very negative information if she is willing to override her desire to rebalance.

I find, however, that the evidence does not support the rebalancing explanation of my main result. When an insider sells a large fraction of her shares at a small gain or at a small loss, she is unlikely to be motivated by rebalancing concerns. However, I find that large liquidations at a small loss predict far more negative returns than large liquidations at a small gain. This casts doubt on the rebalancing story.

Another possible source of aversion to realizing losses that may be driving
my result is realization utility. Under this view, investors derive utility directly from realizing gains and losses: they experience a positive burst of utility when they realize a gain, a burst whose size depends on the size of the gain realized, and a negative burst of utility when they realize a loss. A sale of stock at a loss is then particularly informative about future returns: the investor must have information that is so negative as to override the pain she feels when she sells at a loss.

Among all the explanations I consider, realization utility is the most consistent with the evidence I present. I am able to go one step further, and to use my data on company insiders to shed light on the source of realization utility. One view, the “heuristic” view, is that insiders feel pain when they sell an asset at a loss because they have in mind a rule of thumb, namely that selling assets at a loss is a bad idea. Another view, the “cognitive dissonance” view, is that investors feel pain when they sell an asset at a loss because doing so forces them to admit that their earlier purchase decision was a mistake.

The company insider data allows me to distinguish these views. When insiders acquire a position in a stock, they can do so in one of two ways: they may actively purchase shares or they may be endowed with shares. Under the dissonance view, an investor will not find it painful to sell shares she has been endowed with: since there was no active purchase decision, she does not have to blame herself for a trade gone bad. As a result, a sale of endowed shares at a loss should be no more informative about future returns than a sale of endowed shares at a gain. Under the heuristic view, however, a sale of endowed shares at a loss will be more informative than a sale of endowed shares at a gain: the investor finds it painful to sell even endowed shares at a loss. I test this prediction in the data in two ways, and find evidence in favor of the dissonance view.

Shefrin and Statman (1985) suggest that an investor opens (closes) a mental account when she purchases (sells) a stock, and then evaluates the transaction at the moment of sale. As such, the realization of gains/losses becomes a determinant of overall utility. Similarly, Thaler (1999) writes: “one clear intuition is that a realized loss is more painful than a paper loss. When a stock is sold, the gain or loss has to be ‘declared’ both to the tax authorities and to the investor (and spouse).” Barberis and Xiong (2012) and Ingersoll and Jin (2013) incorporate these ideas into formal models to explain a number of puzzling facts. Frydman et al. (2014) find neuroscientific evidence largely consistent with realization utility.
In summary, then, my basic finding – that a sale of company stock by an insider at a loss has more negative predictive power for future returns than a sale at a gain – is most consistent with realization utility, in other words, with the view that people experience pain when they close out a position at a loss. This, in turn, means that when they do close out a position at a loss, they must have particularly negative information, information which manifests itself in low stock returns over the next few months.

To test my hypothesis that a sale by an informed trader has greater information content when it represents a realized loss, I focus on the trading of company insiders, in part because the data on their trading is of higher quality. I also conduct similar tests to those described above using data on the trading of mutual funds. These tests are unlikely to be as powerful: I observe mutual fund trades only on a quarterly basis, and a good deal of selling by funds is likely driven by liquidity considerations – for example, in response to fund outflows. Perhaps consistent with this, I find that, in the case of mutual fund trades, the results go in the direction predicted by my hypothesis, but are not as significant as the results for company insiders.

The paper proceeds as follows. Section 2 briefly reviews the related literature. Section 3 details the data used. Section 4 presents results using the trades of company insiders. Section 5 documents results using the trades of mutual fund managers. Section 6 concludes.

2 Related literature

There is a large empirical literature on whether the trading activity of corporate insiders predicts returns in the cross-section. Seyhun (1998) reviews the evidence and concludes that insider trades contain predictive power for future returns. He notes that the information content of insider trades is higher when insiders purchase. Similarly, Lakonishok and Lee (2001) argue that the informativeness of insider trades comes from purchases, not sales. Finally, Jeng,

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5Specific articles include Lorie and Niederhoffer (1968), Rozell and Zaman (1988), Lin and Howe (1990), and Bettis, Vickrey, and Vickrey (1997).
Zeckhauser, and Metrick (2003) highlight that while insider purchases earn abnormal returns, insider sales do not. In general, the literature attributes the weak predictive power of sales to the fact that sales are often driven by liquidity and diversification concerns—not private information. Cohen, Malloy, and Pomorski (2012) develop a filter based on trading patterns that decodes whether a sale is likely to be informative (opportunistic) or not (routine). The authors show that opportunistic sales have predictive ability for future returns.  

The conditioning variable I suggest is motivated by the large literature on the aversion to realizing losses. Numerous researchers have documented this investor tendency. For example, Odean (1998) documents an aversion to realizing losses in a data set of 10,000 trading accounts from a large discount brokerage. Genesove and Mayer (2001) find an aversion to realizing losses in the downtown Boston housing market. Grinblatt and Keloharju (2001) obtain data on the trading of individuals and institutions in the Finnish stock market and find that investors are reluctant to sell at a loss. Frazzini (2006) documents this behavior in mutual fund managers. Hartzmark and Solomon (2012) look at a set of NFL betting contracts at Tradesports.com and uncover evidence consistent with the disposition effect.  

In this paper, I argue that, as a consequence of this aversion to realizing losses, insider sales at a loss will have more predictive power for returns than sales at a gain. After confirming this prediction, I dig more deeply into what is driving my result, and, in particular, into the source of the aversion to realizing losses. There are a number of theoretical explanations for this aversion. Odean (1998) notes that rebalancing is a possible explanation, but provides evidence against it. Another possible explanation is a belief in mean-reversion. However, Weber and Camerer (1998) and Hartzmark and Solomon (2012) provide evidence

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6 Cheng, Nagar, and Rajan (2007) show that sales filed under Form 5, which allow for delayed disclosure, predict negative future returns. Marin and Olivier (2008) show that insider sales peak months before a large drop in the stock price. Jagolinzer (2009) looks at the trades of insiders who pre-specify sales using 10b5-1 plans and finds that sale plans are terminated before good performance.

7 There is indirect evidence to suggest that corporate insiders are averse to selling at a loss. Rozell and Zaman (1998), Lakonishok and Lee (2001), and Jenter (2005) document that corporate insiders are contrarian investors.
against this view. Barberis and Xiong (2012) show that realization utility – the notion that investors derive utility directly from realizing gains and losses – and time discounting can explain the disposition effect and a number of other puzzling facts. Finally, Chang, Solomon, and Westerfield (2014) provide evidence for the view that investors are averse to realizing losses because it is painful to admit that a prior purchase decision was a mistake.

3 Data and reference price construction

To conduct the analysis, I collect data from several sources. I obtain return information, monthly closing prices, split-adjustments, and daily low/high/closing prices from CRSP. Other firm-level information comes from the CRSP/Compustat Merged database. I consider ordinary common shares listed on the AMEX, NASDAQ, or NYSE. Following Shumway (1997), I replace missing delisting returns with a return equal to -0.3 for performance-related delistings. I construct a book-to-market control equal to the log value of common equity divided by market capitalization, where market capitalization is equal to the quarterly closing price times the number of common shares outstanding. I only consider observations that have a pre-log book-to-market ratio greater than 0 and less than or equal to 100. Size is calculated as the log value of market capitalization. I construct a control for momentum by calculating the previous year’s return, excluding the most recent month (i.e. I use the return from \((t-12)\) to \((t-1)\)). To mitigate any microstructure effects, I exclude observations where the month-end share price is below one dollar from my analysis. I download factor data from Kenneth French’s website.

I obtain insider data from Thomson-Reuters. The SEC requires corporate insiders, or “a company’s officers and directors, and any beneficial owners of more than ten percent of a class of the company’s equity securities...”, to file their trades. I exclude observations with a cleanse indicator equal to A or S, as these indicate a failed cleansing attempt. I consider insider trades with a transaction

\[\text{8I do not consider REITs, closed-end funds, ETFs, or Americus Trust Components. I consider ordinary common shares with a share code equal to 10 or 11.}\]
code equal to P, S, or A from 1986 to 2013. That is, I consider open market purchases, open market sales, and grants or award transactions (hereafter, endowed shares), respectively. From here on, when I refer to a transaction by an insider, I am referring to one of these three types of transactions. I aggregate trades by personid, transaction date, and transaction code. I use a share-weighted-average, split-adjusted transaction price to compute the daily transaction price. If the transaction/endowed price is unreported, lower than the daily low price, or higher than the daily high price, I use the split-adjusted closing price for the corresponding day.

I obtain mutual fund holdings from the Thomson-Reuters Mutual Fund Holdings database (TRMFH). Mutual funds are required to report holdings only twice a year, but a large number file quarterly reports. To limit my sample to actively managed equity funds, I apply the following filters. I only consider funds with an investment objective code equal to aggressive growth, growth, growth and income, unclassified, or missing. I gather index fund flags and each fund’s ratio of equity holdings to total net assets from the survivorship-bias free CRSP mutual fund database. Using the MFLinks file, I merge this data with TRMFH. I drop all funds that are flagged as index funds, and all observations where the ratio of equity holdings to total net assets is less than 75 percent. To clean the data, I drop all observations where the total net assets reported by TRMFH and CRSP differ by a factor of more than two, where total net assets is missing, and where the total net assets reported by CRSP is less than a million dollars. I replace the number of shares a fund holds with a missing value if the number of shares is greater than the number of shares outstanding, or if the value from that one position is greater than the listed value of the entire portfolio. TRMFH includes a report date for which the portfolio holdings are valid. For funds with more than one piece of holding data per month, I use the latest piece of data. I use a “transaction price” equal to the split-adjusted closing price from the month of the report date. If a fund liquidates its entire position in a stock, I assume that the liquidation took

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9I also include private transactions as after May 1991 private transactions use the same codes as open-market transactions.

10If the split-adjustment value is missing, I do not make any adjustments for splits.
place a month after the last file date.\textsuperscript{11}

3.1 Reference prices

My prediction is that a sale of stock by an informed investor that represents a realized loss is a more negative signal for the stock’s future return than a sale of stock by an informed investor that represents a realized gain. To test this hypothesis, I need to define “realized gain” and “realized loss”. Presumably, an insider thinks of a sale as a realized gain if the price at which she sells is higher than some reference price she has in mind, and as a realized loss if the price is below the reference price. Therefore, to define “realized gain” and “realized loss”, I need to specify what this reference price is.

For insiders, I consider a number of plausible reference prices. I list them below, along with details of their construction, and then discuss them. Recall that an insider can acquire a position in her firm’s stock in one of two ways: she can actively purchase shares; or she can be endowed with them. When I use the term “purchase price”, I am referring to the weighted-average split-adjusted purchase price from the day of purchase; when I use the term “endowed price”, I am referring to the weighted-average split-adjusted price recorded on Form 4 for grants or awards on the day of endowment; and, finally, when I use the term “acquisition price”, I mean either a purchase price or endowed price.\textsuperscript{12}

The reference prices I use in the case of company insiders are:

\textbf{Most recent purchase price.} I look at the most recent date on which the insider actively purchased shares of company stock and take the reference price to be the purchase price from that day.

\textbf{Most recent endowed price.} I look at the most recent date on which the insider received shares of company stock and take the reference price to be the price from

\textsuperscript{11}Thomson Reuters includes a file date every quarter where the holding could be valid.

\textsuperscript{12}If the purchase price or endowment price is missing, I use the day’s closing price. Weights are assigned by number of shares purchased. If the most recent purchase occurs on the same day as the most recent endowment, I take the weighted-average of the two prices.
that day.

**Most recent acquisition price.** I look at the most recent date on which the insider acquired shares of the stock, whether through purchase or endowment. I take the reference price to be the acquisition price on that day.

**Weighted-average purchase price.** I look at the last 100 transactions of any kind that the insider made in the stock, whether purchases, sales, or endowments. From these 100 transactions, I pick out the dates on which the insider actively purchased shares of the stock; let’s say these purchases cover 20 dates. I take the reference price to be the weighted-average purchase price across the 20 dates.

**Weighted-average acquisition price.** I look at the last 100 transactions of any kind that the insider made in the stock, whether purchases, sales, or endowments. From these 100 transactions, I pick out the dates on which the insider acquired shares of stock, whether through purchase or endowment; let’s say these acquisitions cover 30 dates. I take the reference price to be the weighted-average acquisition price across the 30 dates.

**Moving-average price.** I take the average of the previous six split-adjusted month-end prices.

**Experience-based weighted-average price.** I compute the length of time for which the insider has been transacting in the company stock; in other words, I find the insider’s first purchase, sale, or award/grant in the stock, and compute how long ago it was. I then put the insider into one of four categories and, depending on the category she is in, assign her a particular reference price.

- **Length of trading history below six months.** For each of the past six months, I record the split-adjusted month-end stock price. The reference price is the average of these six prices.

- **Length of trading history greater than six months and less than one year.** For each of the past twelve months, I record the split-adjusted month-end stock price. The reference price is the average of these twelve prices.
• *Length of trading history greater than one year and less than 1.5 years.* For each of the past eighteen months, I record the split-adjusted month-end stock price. The reference price is the average of these eighteen prices.

• *Length of trading history greater than 1.5 years.* For each of the past twenty-four months, I record the split-adjusted month-end stock price. The reference price is the average of these twenty-four prices.

A number of my reference prices depend on previous purchase prices. Several papers have suggested that purchase prices are natural reference prices. For example, Shefrin and Statman (1985) suggest that, when an investor buys a stock, a mental account is opened, one that closes only when she eventually sells the stock, at which point she evaluates the transaction by comparing the sale price to the purchase price. Similarly, Barberis and Xiong (2012) suggest that people think of their investing history as a series of investing episodes, each characterized by the name of the asset, the purchase price, and the sale price (“I bought IBM for 80 dollars and sold it for 120 dollars”). As indicated above, I use the most recent purchase price as a reference price, but also a weighted-average price across all purchases. Some investors may use the weighted-average price as their reference price because, by comparing it to the current price, they get a fairly accurate sense of whether they have actually earned a profit on the stock. For other investors, the most recent purchase price may be more salient than other purchase prices; as a result, it becomes their reference price.

I also consider reference prices that take account of endowed prices. One looks at the most recent endowed price, another looks at the most recent acquisition price, and the third is a weighted-average of acquisition prices. In Section 4.9, I argue that, whether or not the endowed prices enter into the reference price depends on the underlying source of realization utility. Indeed, I use the results I obtain for different reference prices as a way of identifying this underlying source.

The final two reference prices are somewhat different: they are time-series averages of recent monthly stock prices. Rather than specifically remembering purchase prices, the insider may simply have a rough sense of what the typical stock price has been in recent periods. The first reference price in this category, the
moving-average price, proxies for this by looking at the average of the previous six month-end closing prices.\textsuperscript{13} Motivated by the growing literature on the importance of experience in financial decisions (e.g. Malmendier and Nagel (2011)), I also consider an “experience-based weighted-average price”, which ties the time-series average for the reference price to the period the insider has been transacting. I look back at most two years in computing this average. For an insider who has been transacting in the company for years, it seems less likely that stock prices from a long time ago will enter into the reference price, either because the insider’s memory does not stretch that far back, or because she slowly adapts to new stock price levels over time.

The seven reference prices listed above apply to the trading of company insiders, my principal focus in this paper. In Section 5, I also test my hypothesis using data on mutual fund trades. In that analysis, I use the single reference price described below:

**FIFO-based weighted-average purchase price.** I use a weighted-average of all purchase prices. I adjust for sales by using FIFO (first in, first out) accounting. For example, suppose an investor purchased 200 shares at date 1 for a price of 30 dollars and another 100 shares at date 2 for 40 dollars. Then, at date 3, the investor sold 250 shares. Under FIFO, of the 250 shares sold, 200 come from the shares purchased at date 1 and 50 come from the shares purchased at date 2. At date 4, the investor’s reference price would be 40 dollars.

A mutual fund manager can only be endowed with shares once, at the start of her tenure as the fund’s manager. As such, I do not consider reference prices related to endowed shares. I also do not use reference prices related to time-series averages of recent monthly stock prices. I ignore these reference prices as I only observe quarterly or semi-annual holdings data and do not have a good proxy for the time of sale. The insider-analog of the reference price I do use is the weighted-average purchase price. I do not use FIFO accounting for insiders as I ignore some of their transactions (e.g. derivative transactions).

\textsuperscript{13}The length of six months is motivated by the short swing rule, which says that insiders cannot sell for a profit within six months of a purchase. The rule is discussed in Section 4.5.
4 Company insiders

In this section, I examine the trades of company insiders. I first test my prediction that a sale at a loss predicts more negative returns than a sale at a gain. Having confirmed my prediction, I examine alternatives to my hypothesis that my result is driven by an aversion to realizing losses. After finding evidence that the result is driven by an aversion to realizing losses, I examine potential drivers of this aversion.

4.1 Disposition effect

Central to my prediction is the premise that insiders are averse to selling at a loss. If this is the case, the proportion of losses realized by insiders should be less than the proportion of gains realized by insiders. I consider a panel of all insider-firm combinations. I include monthly observations for each insider from the month of her first transaction at the firm to the month of her last transaction at the firm. I calculate the proportion of losses realized by dividing the number of months when an insider sold at a loss by a proxy for the number of months when the insider could have sold at a loss. The proxy I use is the number of months when the previous month-end price is below the insider’s reference price. In Table 1, I present the PLR, or the proportion of losses realized, and the PGR, or the proportion of gains realized, for two reference prices that I focus on throughout my analysis, the previous purchase price and the previous six-month moving-average price. I find significant evidence of the disposition effect. For example, I find that, relative to the previous purchase price, the PLR is 2.23 percent and the PGR is 4.62 percent. The difference is statistically significant at the one percent level.\footnote{This result adds to a recent literature which shows that even “sophisticated” investors exhibit a disposition effect. Frazzini (2006) documents this behavior in mutual fund managers. Von Beschwitz and Massa (2014) show that short sellers exhibit the disposition effect. Kallunki, Nilsson, and Hellström (2009) document the disposition effect in the trades of Swedish insiders.}

\footnote{Individuals and blockholders are sometimes insiders at multiple firms over the same period; this will result in duplicate insider-month observations.}
4.2 Firm-level regressions

The central prediction of this paper is that insiders’ realized losses have more information content than their realized gains. To test this, I examine the predictive power of realized losses relative to realized gains for the future one-month return. I run pooled OLS regressions with month fixed-effects.\textsuperscript{16} Specifically, I estimate the following equation for firm \( i \) in month \( t \):

\[
\text{Return}_{i,t \rightarrow t+1} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \\
\beta_6 \text{Sale Below Reference Price}_{i,t} + \beta_7 \text{Sale Above Reference Price}_{i,t} + \\
\beta_8 \text{Previous Month-End Price Below Reference Price}_{i,t} + \\
\beta_9 \text{Capital Gains Overhang}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}. 
\]  

(1)

I estimate the equation using a sample of all firm-month observations since 1986 for firms that have at least one purchase, sale, or endowment of shares. The dependent variable is the return of stock \( i \) from the end of month \( t \) to the end of month \( t + 1 \). The most important independent variables are “Sale Below Reference Price” – a dummy which takes a value of one if an insider in firm \( i \) sold stock at a loss relative to the reference price in month \( t \) – and the analogous “Sale Above Reference Price”. My prediction is that \( \beta_6 \) is less than \( \beta_7 \). In other words, I predict that a sale at a loss has more negative predictive power for subsequent returns than a sale at a gain.

Before turning to the results, I first explain the other independent variables in the regression. I control for the previous month return, the previous year return, excluding the most recent month, the book-to-market ratio, and the size of the firm to ensure that my results are not driven by the short-term reversal phenomenon, the momentum anomaly, the value anomaly, or the size anomaly, respectively. I also control for the capital gains overhang (CGO), which, for a given firm, is a measure of the average capital gain embedded in investors’ holdings of the firm’s stock. Grinblatt and Han (2005) and Frazzini (2006) argue that, as a consequence\textsuperscript{16} I find similar results when I run Fama-MacBeth regressions. However, the sample is very limited in earlier years; hence, early observations could drive the result.

\textsuperscript{16}
of the disposition effect, CGO will predict subsequent stock returns; they confirm this prediction in the data. Since CGO is likely correlated with my “Sale Below Reference Price” and “Sale Above Reference Price” variables, it is important to control for it in my tests. I construct a capital gains overhang control using data on actively managed mutual fund holdings. To calculate the value of this control, I first calculate an aggregate reference price equal to

\[ \frac{\sum_{n=0}^{t} V_{t,t-n} P_{t-n}}{\sum_{n=0}^{t} V_{t,t-n}}, \]  

(2)

where \( V_{t,t-n} \) is the number of shares at time \( t \) that are still held by the period \( t - n \) purchasers and \( P_t \) is the stock price at the end of month \( t \). I use FIFO (first in, first out) accounting to determine which period shares are held by a fund at any particular time. I then define capital gains overhang as the percent deviation of the aggregate reference price from the current price. Specifically, capital gains overhang is equal to

\[ \frac{P_t - RP_t}{P_t}. \]  

(3)

When I use a reference price based on the average(s) of month-end prices, I also include a dummy (dummies) that equals one if the previous month-end closing price was below the reference price(s). This serves as an attempt to ensure that my results are not driven simply by the opportunity to sell at a loss, rather than by an actual sale at a loss.

Finally, I also include month fixed effects as there could be common shocks within a period (e.g. changes in investor discount rates or investor sentiment) as well as within-month correlation across firms in my dummy variables. By month fixed effects, I mean month-year fixed effects.
may have negative one-month returns as a result of aggregate market shocks.\textsuperscript{19} To address correlation with an industry/investment category in a particular month, I cluster standard errors by month.

Having defined the control variables, I turn to the results. I consider all seven reference prices defined in Section 3.1. The results, presented in Table 2, provide robust evidence that sales at a loss have more predictive power than sales at a gain. All reference prices yield statistically significant results consistent with my prediction that $\beta_6 < \beta_7$. The reference price that yields the most statistically significant result is the six-month moving average. I find that a sale below this reference price predicts a return 59 ($t = -6.94$) basis points lower than all other firm-months in my sample. On the other hand, a sale above the moving-average reference price predicts a return only 1 ($t = -0.16$) basis point lower. I reject the null hypothesis that the two are equal at the one-percent level (F-statistic=25.39). The reference price that least supports my hypothesis is the most recent acquisition price. Sales below the most recent acquisition reference price predict returns 31 basis points lower ($t = -3.44$) while sales above the acquisition price predict returns 2 basis points lower ($t = -0.26$). However, even here, I reject the null hypothesis that the two are equal at the five-percent level (F-statistic=5.52).

Under my hypothesis, it is plausible that firm-months with more than one sale at a loss will predict more negative returns than firm-months with exactly one sale at a loss. To test this, I add some dummy variables to equation (1). Specifically, I add dummy variables that equal one if there was more than one sale at a loss (gain) relative to the six-month moving-average reference price in the

\textsuperscript{19}For example, tax considerations likely motivate insiders to realize losses in December. Additionally, there is likely correlation across firms as to when bonuses are paid/stock compensation vests, which would influence selling behavior, and also likely correlation as to when firms’ insiders are trading at a loss.
associated firm month.\textsuperscript{20} I estimate the following equation for firm $i$ in month $t$:

$$\text{Return}_{i,t} \rightarrow t+1 = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t}$$

$$+ \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \beta_6 \text{Sale Below Reference Point}_{i,t} +$$

$$\beta_7 \text{Sale Above Reference Point}_{i,t} + \beta_8 \text{Multiple Sales Below Reference Price}_{i,t} +$$

$$\beta_9 \text{Multiple Sales Above Reference Price}_{i,t} +$$

$$\beta_{10} \text{Previous Month-End Price Below Reference Price}_{i,t} +$$

$$\beta_{11} \text{Capital Gains Overhang}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}.$$  

(4)

My prediction is that firm-months with more than one realized loss should have more negative predictive power than firm-months with only one realized loss. That is, I predict that $\beta_8 < 0$. The results are consistent with this prediction. I estimate $\beta_8$ equal to $-0.233$ ($t = -1.94$) and $\beta_6$ equal to $-0.474$ ($t = -5.03$). That is, a firm with more than one insider sale below the reference price in a particular month is associated with a return 23 basis points lower than a firm that has exactly one sale below the reference price. Interestingly, the coefficient on $\beta_9$ is practically zero.

The predictive power of realized losses allows for the construction of portfolio strategies that, at least before transaction costs, earn high alphas. At the beginning of each month, I construct equal-weighted and value-weighted portfolios that go long a firm if one of its insiders made a purchase and go short a firm if one of its insiders sold \textit{at a loss}.\textsuperscript{21} As shown in Table 3, when I use the previous purchase price as a reference price, I find that an equal (value)-weighted portfolio delivers four-factor alphas of 165 (108) basis points per month with a t-statistic equal to 9.54 (4.36). By comparison, an equal (value)-weighted portfolio that goes long when an insider buys and goes short when an insider sells earns four-factor alphas of only 94 (40) basis points per month with a t-statistic of 7.89 (2.99). As the most direct test of my prediction, I look at a portfolio that goes long when an insider sells above their previous purchase price and goes short when an insider sells

\textsuperscript{20}I use this reference price as it yielded the largest F-statistic in the initial regression.

\textsuperscript{21}I focus on two reference prices: the previous purchase price, as it is perhaps the most natural reference price, and the six-month moving average, as it is the reference price that delivers the most statistically significant result in Table 2.
below their previous purchase price. I find that this equal (value)-weighted portfolio earns four-factor alphas of 77 (73) basis points per month with a t-statistic of 3.56 (2.59). I list other portfolio alphas in Table 3.

To examine the persistence of the effect I am documenting, I extend the pooled OLS analysis in Table 2 to look at predictability over longer horizons. Specifically, I estimate the following equation for firm $i$ in month $t$:

$$
\text{Return}_{i,t-t+6} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \beta_6 \text{Sale Below Reference Price}_{i,t} + \\
\beta_7 \text{Sale Above Reference Price}_{i,t} + \beta_8 \text{Capital Gains Overhang}_{i,t} + \\
\beta_9 \text{Previous Month-End Price Below Reference Price}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}.
$$

The equation is the same as equation (1) except that I use a different dependent variable. I find significant evidence that a sale at a loss has more predictive power for future six-month returns than a sale at a gain. I present the results in Table 4. Using the six-month moving average as the reference price, I find that a sale below the reference price predicts six-month returns 181 basis points lower ($t = -9.51$) than all other firm-months in my sample while a sale above the reference price predicts returns 10 basis points higher ($t = 0.54$). The difference is statistically significant at the one-percent level (F-statistic$= 36.80$). When I use the previous purchase price as a reference price, I find that a sale below the purchase price predicts a six-month return 238 basis points lower ($t = -5.04$) than all other firm-months in my sample while sales above the purchase price predict a six-month return only 14 basis points lower ($t = 0.62$). The difference is statistically significant at the one-percent level (F-statistic $= 15.85$). In Figure 1, I graph the predictive power of sales at a loss and sales at a gain for returns up to six months. These results suggest that the original finding in Table 2 is persistent.

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22I focus on two reference prices: the previous purchase price, as it is perhaps the most natural reference price, and the six-month moving average, as it is the reference price that delivers the most statistically significant result in Table 2. Again, I use a sample of all firm-month observations since 1986 for firms that have at least one purchase, sale, or endowment of shares.
4.3 The size of realized losses and realized gains

A reasonable assumption is that investors are more averse to realizing large losses compared to small losses and, similarly, more keen to realize large gains as opposed to small gains. For example, rebalancing motives are likely strongest when the stock is trading at a large gain and weakest when the stock is trading at a large loss. As another example, Barberis and Xiong (2012) and Ingersoll and Jin (2013) posit that realization utility is proportional to the size of the gain or loss. As a result, I predict that a sale of stock at a large loss will convey more information about future returns than a sale at a small loss.

To examine this prediction, I divide both the gain and loss region into two sub-regions. I then replace the sale dummies from equation (1) with four dummies that equal one if a sale falls into the specified sub-region. I then compare the predictive power of a sale in each subregion. I run pooled OLS regressions of the following form for firm \( i \) in month \( t \):

\[
\text{Return}_{i,t-t+1} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \beta_6 \text{Large Realized Gain}_{i,t} + \beta_7 \text{Small Realized Gain}_{i,t} + \beta_8 \text{Small Realized Loss}_{i,t} + \beta_9 \text{Large Realized Loss}_{i,t} + \beta_{10} \text{Capital Gains Overhang}_{i,t} + \text{Price Dummies}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}.
\]

(6)

All trade variables are dummies that equal one if the stated trade occurred in the associated firm-month. The Large and Small descriptors refer to the subset of the loss/gain region where the sale occurred. I use the six-month moving average as the reference price.\(^{23}\) I subdivide the gain and loss regions by using cutoffs twenty percent above and twenty percent below the six-month moving average, respectively.\(^{24}\) I create three price dummies, each associated with one of three sub-regions (I exclude one), that equal one if the previous month-end price falls into the specified region. I predict that \( \beta_9 < \beta_8 < \beta_7 < \beta_6 \). In other words,

\(^{23}\)The six-month moving-average delivers the most statistically significant result in Table 2.

\(^{24}\)A ten percent cutoff yields similar results.
I expect that large realized losses will predict more negative returns than small realized losses and, similarly, that small realized gains will predict more negative returns than large realized gains.

I present the results in Table 5. In line with my prediction, I find that sales at large losses are associated with more negative predictive power than sales at small losses and sales at large gains are associated with less negative predictive power than sales at small gains. Specifically, I estimate $\beta_6$ equal to 0.27 ($t=1.93$), $\beta_7$ equal to -0.14 ($t=-2.08$), $\beta_8$ equal to -0.51 ($t=-6.97$), and $\beta_9$ equal to -0.70 ($t=-3.00$).\(^{25}\)

### 4.4 Individual-level regressions

Having confirmed my prediction that sales at a loss have more predictive power than sales at a gain, I next examine whether an aversion to realizing losses is driving my result. That is, does my basic result stem from the fact that insiders require a stronger negative signal to sell at a loss than to sell at a gain? Over the next three subsections, I test alternatives to this view. In this section, I examine investor heterogeneity. In the next section, I look at whether my basic result is a consequence of the short swing rule. Finally, I examine whether my result stems from a correlation with the price path.

Insiders surely differ in the sophistication of their trading. It seems possible that more sophisticated traders will make trades that are more informative about future returns, and also that they will exhibit the disposition effect less, because they know it to be a mistake. If this is the case, we would then observe that sales at a loss are more informative than sales at a gain, but this would not be driven by any aversion to realizing losses. To address this concern, I estimate models with individual-firm fixed effects.\(^{26}\) That is, I compare the predictive power of realized losses relative to realized gains within each insider-firm combination.

I consider a panel of all insider-firm combinations. I include monthly ob-

\(^{25}\)When I look at the predictability at a six-month horizon, a sale in the large gain region is no longer statistically significant ($t=0.54$) and predicts a positive return of only 22 basis points.

\(^{26}\)That is, I include a dummy for each individual-firm combination in the sample.
ervations for each insider from the month of her first transaction at the firm to
the month of her last transaction at the firm. I restrict the sample to the set of
months where there was a sale. Then, I estimate models with individual-firm fixed
effects. Again, I control for common shocks within a particular month by using
month fixed effects. I cluster standard errors by month. Specifically, I estimate
the following equation for individual-firm $i$ in month $t$:

\[
\text{Return}_{i,t} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Sale Below Reference Price}_{i,t} + \beta_6 \text{Capital Gains Overhang}_{i,t} + \gamma_1 \text{Individual-Firm} + \gamma_2 \text{Month} + \epsilon_{i,t}.
\]

I use the moving-average reference price as this reference price delivers the
most statistically significant result in Table 2. I predict that $\beta_5 < 0$. That is,
I expect to see evidence within-insider that sales at a loss have more predictive
power than sales at a gain.

I present the results in the first column of Table 6; I discuss the other
columns in the table in later sections. I find evidence that the basic result is not
due to individual differences. Namely, I find that individual-firm-months with a
sale below the moving-average predict a one-month return 57 basis points lower
($t=-3.31$) than all other individual-firm-months.

### 4.5 Short swing rule

Having ruled out insider heterogeneity as the driver of my basic result, I
now examine whether it may instead be driven by the short swing rule. This rule
(15 U.S. Code 78p) states that all profits realized by an insider from executing two
offsetting transactions within a six-month period (a buy and a subsequent sale or

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27 Instead of subtracting an average monthly return, or index return, from the dependent
variable, I use the fixed effects estimator as this estimator is consistent (Gormley and Matsa
(2014)). I overcome the computational difficulties that arise when estimating models with high-
dimensional fixed effects by using the Stata procedure reg2hdfe designed by Guimaraes and
Portugal (2010).
a sale and a subsequent buy) are recoverable by the issuer. As such, it is unlikely that an insider would purchase or sell stock if she had any intention to complete an offsetting transaction in the near future.

Therefore, in the six months following a purchase, it is unlikely that an insider will feel the need to sell shares for liquidity or diversification reasons. As such, sales executed shortly after purchases are presumably very informative. And, as a consequence of the regulatory environment (i.e. the short swing rule), insiders are strictly penalized for realizing gains. This could drive my result as the legal environment prevents realized gains and permits realized losses during a window where insiders likely only make informed trades.

I test this alternative explanation by looking at the information content of realized losses made at least six months after the most recent purchase and the information content of realized gains made at least six months after the most recent purchase. I construct a dummy variable that equals one if there was a realized loss (gain) at least 180 days after the most recent purchase. I find that a sale below the purchase price predicts returns 59 basis points lower than all other firm-months while a sale above the purchase price predicts returns 7 basis points lower. The difference is still statistically significant at the one-percent level (F-statistic = 7.37). By comparison, in Table 2, when I look at all realized losses and sales, I find that a sale below the purchase price predicts a return 72 basis points lower than all other firm-months while a sale above the purchase price predicts a return only 9 basis points lower. This suggests that the short swing rule plays at most a minor role in explaining my results.

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28 “For the purpose of preventing the unfair use of information which may have been obtained by such beneficial owner, director, or officer by reason of his relationship to the issuer, any profit realized by him from any purchase and sale, or any sale and purchase, of any equity security of such issuer (other than an exempted security) or a security-based swap agreement involving any such equity security within any period of less than six months, unless such security or security-based swap agreement was acquired in good faith in connection with a debt previously contracted, shall inure to and be recoverable by the issuer, irrespective of any intention on the part of such beneficial owner, director, or officer in entering into such transaction...”
4.6 Opportunistic and routine traders

As the final alternative to the hypothesis that my basic result is driven by insider aversion to realizing losses, I examine whether this result stems from a correlation with the price path. For example, the timing of an insider trade at a loss may be correlated with the recent path of the stock price in some way that is not fully captured by my controls for short-term reversals, momentum, and capital gains overhang. To examine this explanation, I consider a placebo test. I test whether there is differential predictive power for future returns between uninformed realized losses and uninformed realized gains.

Cohen, Malloy, and Pomorski (2012) use a filter to distinguish informative trades from uninformative trades. The authors label informative trades “opportunistic” and uninformative trades “routine”. They show that “opportunistic” sales contain all the information content in the universe of sales. Since routine sales do not have any informational content, I do not expect there to be a difference in predictive power for future returns between routine sales at a loss and routine sales at a gain. Of course, I still expect there to be a significant difference between the information content of opportunistic realized losses and opportunistic realized gains.\(^{29}\)

Following Cohen, Malloy, and Pomorski (2012), I consider all open-market purchases and sales. I apply their filter by classifying insiders at the beginning of each year as opportunistic or routine. An insider is classified as a routine trader if she made a trade in the same month for three consecutive years.(e.g. an insider who made a trade in April 2001, April 2002, and April 2003 would be considered a routine trader from Jan 2004 - Present). All insiders who are not classified as routine are classified as opportunistic.\(^{30}\) I restrict my sample to firm-months after

\(^{29}\)I use the six-month moving average as the reference price since it does not require a trading history and therefore does not interfere with Cohen, Malloy, and Pomorski’s (2012) identification of routine and opportunistic traders.

\(^{30}\)I only consider trades by insiders who have three consecutive years of trading history. This makes it possible for an insider to be classified as a routine trader. Feng and Seasholes (2005) show that investor sophistication and trading experience eliminate the reluctance to realize losses; therefore, we may expect the disposition effect, and my main result, to be weaker in this sample.
1989. By definition, opportunistic traders can be re-classified as routine traders at the beginning of each year, but routine traders stay routine. Again, I run pooled OLS regressions with month fixed effects and cluster standard errors by month. For firm $i$ in month $t$, I estimate the model:

$$\text{Return}_{i,t} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Opportunistic Buy}_{i,t} + \beta_6 \text{Routine Buy}_{i,t} + \beta_7 \text{Routine Realized Gain}_{i,t} + \beta_8 \text{Routine Realized Loss}_{i,t} + \beta_9 \text{Previous Month End Price Below Reference Price}_{i,t} + \beta_{10} \text{Capital Gains Overhang}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}.$$ (8)

My prediction is that $\beta_7 = \beta_8$. That is, I do not expect there to be any difference between the predictive power of future returns for realized losses relative to realized gains among routine trades.

I present the results in Table 7. Like Cohen, Malloy, and Pomorski (2012), I find a statistically significant difference between the predictive power of opportunistic sales and routine sales (F-statistic=4.66, p-value=0.0315); I also find that routine sales do not have statistically significant predictive power for future returns. Consistent with my result reflecting the information content of insider sales, I fail to reject the null hypothesis that the predictive power of routine realized gains, -8 basis points, is equal to the predictive power of routine realized losses, -15 basis points. The F-statistic is equal to 0.16 (p-value=0.6919). On the other hand, the difference in predictive power between opportunistic realized gains, -12 basis points, and opportunistic realized losses, -51 basis points, is statistically significant with an F-statistic equal to 5.95 (p-value=0.0152).

4.7 Rebalancing

My maintained hypothesis is that the result in Section 4.2 is driven by the aversion to realizing losses inherent in the disposition effect. In the next three

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31 This allows for a three-year trading history to be built.
sections, I explore possible sources of this aversion to realizing losses, an aversion that makes sales at a loss much more informative than sales at a gain. I first examine a portfolio rebalancing explanation.

Rebalancing motives are an important motive when an investor decides to sell a stock. Unlike taxes, rebalancing motives could differentially encourage investors to sell more at a gain compared to at a loss. After a fall in the share price, the stock likely makes up a smaller fraction of the investor’s portfolio than before. After a rise in the share price, the stock likely makes up a larger fraction of the investor’s portfolio than before. Therefore, rebalancing motives may encourage the investor to sell more after a rise in the share price compared to after a fall in the share price. If so, my result may stem from the fact that realized gains are more likely to be rebalancing trades than realized losses.\(^{32}\)

To test this hypothesis, I compare the predictive power for future returns of complete liquidations at a loss with the predictive power for future returns of complete liquidations at a gain. Complete liquidations are likely not driven by rebalancing motives; as a result, if complete liquidations at a loss predict returns more negatively than complete liquidations at a gain, this would cast doubt on the rebalancing view. Specifically, I estimate the following equation for firm \(i\) in month \(t\), clustering standard errors by month.

\[
\text{Return}_{i,t\rightarrow t+1} = \beta_0 + \beta_1 \text{Short Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \\
\beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \beta_6 \text{Complete Liquidation Below Reference Price}_{i,t} + \\
\beta_7 \text{Complete Liquidation Above Reference Price}_{i,t} + \\
\beta_8 \text{Month-End Price Below Reference Price} + \beta_9 \text{Capital Gains Overhang}_{i,t} + \\
\gamma \text{Month} + \epsilon_{i,t}. 
\]

(9)

If rebalancing motives are driving my result, the prediction is that \(\beta_6 = \beta_7\). While I fail to reject the null hypothesis that the two coefficients are equal, I

\[^{32}\text{In contrast, Kallunki, Nilsson, and Hellström (2009) look at data on Swedish insiders and show that insider selling is most informative for Swedish insiders who have the greatest proportion of wealth allocated to insider stocks. They explain this finding by noting that economic incentives are strongest for these insiders.}\]
find an economically strong difference between the two. I find that a complete liquidation at a loss predicts a one-month return 164 basis points lower than all other firm-months in my sample while a complete liquidation at a gain predicts a one month return 60 basis points lower.\footnote{My sample is all firm-months since 1986 for firms that have at least one sale, purchase, or endowment of shares in the sample.} Given the limited number of complete liquidations in the sample, it is not surprising that the difference between the two coefficients is not statistically significant. (There are only 222 firm-months across the entire sample where an insider completely liquidates her position at a loss.)

If I instead look at liquidations of more than 90 percent of an insider’s holdings (hereafter “large” liquidations), where rebalancing motives probably play a minor role, the difference between the one-month predictive power of sales at a loss (-101 basis points) and sales at a gain (-18 basis points) is statistically significant at the five-percent level (F-statistic=6.27). As another test of the rebalancing view, I compare large liquidations at a small gain to large liquidations at a small loss.\footnote{I use my earlier definition of small gain and small loss. A small gain is less than 20 percent above the reference price and a small loss is less than 20 percent below the reference price.} I re-estimate equation (9), but replace the Complete Liquidations variable with a dummy variable(s) that equals one if there was a large liquidation at a small gain or small loss. I drop the old price dummy (Month-end Price Below Reference Price) and I include new price dummies that equal one if the previous month-end price falls into the small gain or small loss sub-regions. I find that a large liquidation at a small loss predicts a return 97 basis points lower (t=-3.26) than all other firm-months in the sample while a large liquidation at a small gain predicts a return only 29 basis points lower (t=-1.93). The difference is statistically significant at the five-percent level (F-statistic=4.38). I interpret this as evidence that rebalancing is not the main driver of my original result in Table 2.

I address the rebalancing explanation in one final way using the individual-level analysis described in Section 4.4. Dhar and Zhu (2006) find that individual attributes corresponding to financial sophistication attenuate the magnitude of the disposition effect. Therefore, I expect a smaller spread in the predictive power of sales at a loss compared to the predictive power of sales at a gain for more
financially sophisticated insiders. It is plausible that CFOs are more financially sophisticated than other insiders. Therefore, I further limit the data set to the set of individual-firm-months where there was a sale by a CFO. As shown in the second column of Table 6, I find that months with sales at a loss by a CFO predict a return 5 basis points \((t=0.15)\) higher than all other individual-firm-months with a sale by a CFO. That is, the spread between the predictive power of realized losses and realized gains disappears in this financially sophisticated subset of insiders. This is consistent with Dhar and Zhu (2006), and serves as additional evidence against an explanation rooted in rebalancing as there is no reason to expect that rebalancing motives are significantly weaker for CFOs than for other insiders. Indeed, one would expect rebalancing motives to be stronger for CFOs, because rebalancing is something sophisticated people are more likely to do.

4.8 Mean-reversion

Another reason that insiders may be averse to realizing losses is a belief in mean-reversion. Specifically, insiders may believe that the stock price, after falling, is likely to increase. As a result, they require an especially strong negative signal to sell at a loss.

To test this, I look at the predictive power of sales at a loss when the stock price has increased recently. Insiders with a belief in mean-reversion are likely averse to selling after a fall in the stock price and not averse to selling after an increase in the stock price. Therefore, the predictive power of sales at a loss should be less powerful after an increase in the stock price. I estimate equation (1) again, but this time I add two dummy variables. One dummy, “Increase”, equals one if the return in the month prior to trading was positive. The other, “Sale at a Loss After an Increase”, equals one in a particular firm-month if there was an insider who sold below the six-month moving-average when the return in the month prior to trading was positive. Specifically, I estimate the following equation, clustering
standard errors by month.

\[ \text{Return}_{i,t+1} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} \\
+ \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \beta_6 \text{Sale Below Reference Price}_{i,t} + \beta_7 \text{Sale Above Reference Price}_{i,t} + \beta_8 \text{Sale at a Loss After an Increase}_{i,t} + \beta_9 \text{Previous Month-End Price Below Reference Price}_{i,t} + \beta_{10} \text{Capital Gains Overhang}_{i,t} + \beta_{11} \text{Increase}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}. \]  

(10)

Under mean-reverting beliefs, the prediction is that \( \beta_8 > 0 \). Specifically, the prediction is that the predictive power of a sale at a loss will decrease when the recent return is positive.\(^{38}\)

I estimate \( \beta_8 = -0.24 \) (t=-1.69). As the coefficient is not positive, this test provides evidence against an explanation rooted in mean-reverting beliefs.

4.9 An examination of realization utility

Realization utility refers to the simple idea that investors derive utility directly from the act of realizing a gain or loss on an asset. Unlike the other explanations I have considered, this simple idea is consistent with all evidence presented thus far – not just the basic result in Section 4.2, but also, for example, the finding that large realized losses are a stronger signal than small realized losses. Still, the underlying source of realization utility is unclear: Why do investors experience disutility when they close out a position at a loss? In this section, I examine two proposed answers to this question – a heuristic-based explanation and a cognitive dissonance-based explanation.

An investor who sells all of her positions at a gain (loss) makes (loses) money. This observation is the foundation for the heuristic that Barberis and Xiong (2012) argue underlies realization utility. Selling at a gain is good; selling

\(^{38}\)It is important to note that this prediction holds for one particular type of mean-reverting belief, namely, one where people expect mean-reversion at a monthly horizon. Jegadeesh (1990) documents negative first-order serial correlation in monthly stock returns.
at a loss is bad. The investor derives utility from doing something good (realizing gains) and derives disutility from doing something bad (realizing losses).

Another possible source of realization disutility is a reluctance to admit that an earlier purchase decision was a mistake. Instead of admitting a mistake, investors may manipulate malleable, but negative, signals to preserve a positive self-image.\textsuperscript{39} This self-delusion relieves cognitive dissonance. An investor experiences cognitive dissonance, or “the discomfort that arises when a person recognizes that he or she makes choices and/or holds beliefs that are dissonant with each other – actions and/or beliefs that do not fit together”, if she thinks she is a talented investor, purchases stock, and then receives a signal indicating that the purchase was a mistake. Chang, Solomon, and Westerfield (2014) highlight that investors can reduce the discomfort by either admitting their mistake, finding a third-party scapegoat, blaming bad luck, or explaining the bad performance as a temporary setback that will soon be reversed. As many people enjoy holding a positive self-image, admitting a mistake can be painful and a source of realization disutility.

Company insiders are somewhat unique in that they acquire stock in two ways, either by actively purchasing shares or by being endowed with shares.\textsuperscript{40} This distinction allows me to shed light on the underlying source of realization utility. Under the heuristic explanation, a company insider will experience disutility if she sells shares at a loss regardless of whether she purchased the shares or was simply endowed with them. This predicts that a sale at a loss by an insider will be a more negative signal of future returns than a sale at a gain, irrespective of whether the shares were purchased or endowed. On the other hand, under the cognitive dissonance view, the company insider will only feel pain from selling at a loss if the shares that she is selling are shares that she actively purchased; if she was merely endowed with the shares, she has no reason to blame herself for their poor performance. This predicts that a sale of shares by an insider at a loss will

\textsuperscript{39}Mazar, Amir, and Ariely (2012) provide evidence that people delude themselves in order to maintain an image of themselves as honest. Frydman and Rangel (2014) find that one can debias the disposition effect by reducing the saliency of the purchase price.

\textsuperscript{40}Jin and Scherbina (2010) make a similar distinction in mutual fund holdings. The authors compare the holdings of managers who take over a fund with the holdings of continuing fund managers.
be a more negative signal about the stock’s future return than a sale at a gain
only if the shares that the insider sold were shares that she actively purchased.

I test these competing theories by limiting my individual-level panel dataset
to all individual-firm-months where an insider made a sale. I compare the pre-
dictive power of losses realized by purchasers, or individuals who have previously
purchased shares, to all realized losses.\textsuperscript{41} To do this, I construct an interaction
term equal to the realized loss dummy times a purchaser dummy. If the “cognitive
dissonance” explanation holds, the coefficient on this interaction term should be
negative and statistically significant. Of course, insiders who have previously pur-
chased shares are fundamentally different from insiders who have never purchased
shares. To address this, I include insider-firm level fixed effects, thus taking out the
average return predictability of a sale by each insider at each firm. To avoid any
timing effects, I include month fixed effects. Specifically, I estimate the following
equation for individual-firm $i$ in month $t$, and cluster standard errors by month.

\[
\text{Return}_{i,t \rightarrow t+1} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} \\
+ \beta_4 \text{Size}_{i,t} + \beta_5 \text{Sale Below Reference Price}_{i,t} \\
+ \beta_6 \text{Sale Below Reference Price} \ast \text{Purchaser}_{i,t} \\
+ \beta_7 \text{Capital Gains Overhang}_{i,t} + \gamma_1 \text{Individual-Firm} + \gamma_2 \text{Month} + \epsilon_{i,t}.
\]

(11)

The cognitive dissonance view predicts that $\beta_6 < 0$.

I present the results in the third column of Table 6. I find that an individual-
firm-month with a sale at a loss by a purchaser predicts one-month returns 35 basis
points lower ($t = -2.11$) than all other observations in my sample. This result is
consistent with the “cognitive dissonance” view of realization utility.

As an additional test of the cognitive dissonance view, I limit the panel
data set to individual-firm-month observations where there is a sale by an insider
who has both purchased and been endowed with shares at the associated firm.
I compare the likelihood that insiders sell when the price is below the previous

\textsuperscript{41}I use the six-month moving average for comparability and also because it is the reference
price that produces the most statistically significant result in Table 2.
purchase price to the likelihood that they sell when the price is below the endowed price. The “cognitive dissonance” view implies that sales are less likely when the insider is trading at a loss relative to her purchase price than when she is trading at a loss relative to her endowed price. The heuristic view, on the other hand, makes no distinction between the likelihood of a sale in either situation. To address the fact that the information environment may be different when an insider is trading at a loss relative to her purchase price, but not when she is trading at a loss relative to her endowed price, I include firm-month fixed effects and cluster standard errors by firm-month.\footnote{I look at whether the previous month-end price is below the relevant reference price to determine if the insider is trading at a loss.} Explicitly, I estimate the following linear probability model for individual $i$ in month $t$:

$$\text{Sale}_{i,t} = \beta_0 + \beta_1 \text{Sale Below Endowed Price}_{i,t} + \beta_2 \text{Sale Below Purchase Price}_{i,t} + \gamma \text{Firm-Month} + \epsilon_{i,t}.$$ (12)

The results are in the fourth column of Table 6. I estimate $\beta_1 = 0.02$ ($t = 0.19$) and $\beta_2 = -0.29$ ($t = -5.65$). The difference is statistically significant at the one-percent level (F-statistic= 10.00). Economically, a sale is about six-percent less likely when the price is below the purchase price. I interpret this finding, as well as the previous findings in this section, as evidence for a “cognitive dissonance” view of realization utility.

4.10 Purchases

My focus in this paper is on the sales of informed traders. However, a similar argument to the one I use for my prediction about sales also suggests that purchases above the reference price may have more predictive power for future returns than purchases below the reference price.

Insiders may be averse to purchasing shares at a price higher than the reference price – there are a number of potential sources of this aversion.\footnote{This aversion could stem from rebalancing motives, a belief in mean-reversion, or a refusal to admit that an earlier non-purchase was a mistake. Strahilevitz, Odean, and Barber (2011) document that investors prefer to purchase stocks that have decreased in value since a prior sale}
insiders are averse to purchasing shares above their reference price, then they should require an especially strong positive signal to do so. To test this, I estimate the following equation for firm $i$ in month $t^{44}$:

$$\text{Return}_{i,t-t+1} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy Above Reference Price}_{i,t} + \beta_6 \text{Buy Below Reference Price}_{i,t} + \beta_7 \text{Sale Above Reference Price}_{i,t} + \beta_8 \text{Sale Below Reference Price}_{i,t} + \beta_9 \text{Capital Gains Overhang}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}. \quad (13)$$

My prediction is that purchases above the reference price will have more predictive power for future returns than purchases below the reference price. That is, my prediction is that $\beta_5 > \beta_6$. Similar to the sale analysis, I consider a dependent variable equal to the one-month return and a dependent variable equal to the six-month return.

I present results in Table 8. The evidence is mixed. At the one-month horizon, there is little evidence that purchases above the reference price have more predictive power than purchases below the reference price: firm-months with a purchase above the six-month moving average predict a return 71 basis points higher in the following month relative to all other firm-months, while firm-months with a purchase below the six-month moving average predict a return 76 basis points higher. The difference between the two is not statistically significant. When I use the previous purchase price as the reference price, I find that firm-months with a purchase above the reference price predict a return 75 basis points higher in the following month relative to all other firm-months while firm-months with a purchase below the reference price predict a return only 44 additional basis points higher. I can reject the null hypothesis that the two are equal at the 5-percent level with an F-statistic equal to 4.02.

over those that have gained value.

$^{44}$I use two reference prices: the six-month moving average as it yielded the most statistically significant result in Table 2 and the previous purchase price as it is probably the most natural reference price.
At the six month horizon, I find more convincing evidence that purchases above the reference price have more predictive power for future returns than purchases below the reference price. Specifically, I find that firm-months with a purchase above the six-month moving average predict returns over the following six-months that are 256 basis points higher than all other firm-months in my sample while firm-months with a purchase below the six-month moving average predict six-month returns only 69 basis points higher. I can reject the null hypothesis that the two are equal at the one-percent level (F-statistic= 20.32). Similarly, firm-months with a purchase above the previous purchase price predict six-month returns 215 basis points higher than all other observations while firm-months with a purchase below the previous purchase price predict six-month returns 11 basis points lower. This difference is also statistically significant at the one-percent level with an F-statistic equal to 23.63.

These results indicate that, while the market responds positively in the near-term to both sets of purchases, purchases above the reference price have more information content for long-term returns.

5 Mutual fund managers

My hypothesis is that, if an investor is informed and averse to realizing losses, realized losses will have more information content than realized gains. There is evidence to suggest that mutual fund managers are informed traders. Additionally, managers exhibit the disposition effect (Frazzini, 2006). Therefore, within the set of mutual fund trades, I expect sales at a loss to have more information content than sales at a gain.

To test my hypothesis that a sale by an informed trader has greater information content when it represents a realized loss, I have focused on the trades of company insiders, in part because the data on their trading is of high quality. In principle, I can also test my hypothesis using the data on the trades of mutual

\[45\] Berk and Van Binsbergen (2014) use the dollar-value a mutual fund manager adds as a measure of skill and find that this skill exists and is persistent. Additionally, Cremers and Petajisto (2009) show that “active” mutual fund managers earn significant excess returns.
fund managers. However, the reporting requirements for mutual funds are far less strict than the reporting requirements for insiders. I view snapshots of mutual fund holdings on a quarterly, sometimes semi-annual, basis. As such, I do not know the transaction date or the transaction price. Without such key information, there is a lot of noise in any empirical analysis based on these data. Nonetheless, in this section I present the results of testing my hypothesis using actively-managed equity mutual funds.

I use a reference price equal to the weighted-average purchase price. I use FIFO (first in, first out) accounting to determine the shares involved in the construction of the weighted-average purchase price. The “transaction” price is equal to the month-end price of the month when the transaction was reported.

I attempt to control for market conditions correlated with selling at a loss. Therefore, I include controls for momentum and short-term reversals. Additionally, I include a dummy that equals one if the previous month-end price is less than the reference price. Finally, I control for the capital gains overhang measure defined by Frazzini (2006).  

I control for unobserved heterogeneity by including month and fund fixed effects in my analysis. I include month fixed effects as fund managers may realize more losses in months with market-wide lower returns. I also include fund fixed effects as I do not want my results to be driven by any correlation between skill and the propensity to realize losses. Explicitly, I estimate the following regression for firm $i$ at time $t$:

$$
\text{Return}_{i,t-1,t+1} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} + \beta_4 \text{Size}_{i,t} + \beta_5 \text{Sale Below Reference Price}_{i,t} + \beta_6 \text{Sale Above Reference Price}_{i,t} + \beta_7 \text{Price Below Reference Point}_{i,t} + \beta_8 \text{Capital Gains Overhang}_{i,t} + \gamma_1 \text{Fund} + \gamma_2 \text{Month} + \epsilon_{i,t}.
$$

(14)

Again, the sample I use to construct the capital gains overhang measure is slightly different as I only consider actively-managed equity mutual funds.
My prediction is that sales at a loss will predict more negative returns than sales at a gain. Specifically, I expect $\beta_5 < \beta_6$.

I present results in Table 9. Sales at a loss predict returns 33 basis points lower ($t=-3.13$) than all other observation in the sample and sales at a gain predict returns only 7 basis points lower ($t=-1.45$). As noted earlier, I do not have precise data regarding mutual fund trades. As such, I have to make assumptions regarding the trade date, the trading price, and so on. This may contribute to the relative weakness of the result. Additionally, my sample includes not only the discretionary trades I am interested in, but also trades that are forced by fund flows.

To address these issues, I construct dummies based on entire liquidations; that is, sales of entire positions, which are unlikely to be driven by fund flows. Replacing the “Sale Below (Above) Reference Price” variable with a dummy variable that equals one when there is a complete liquidation at a loss (gain), I estimate equation (14) again. I find that a complete liquidation at a loss predicts returns 159 basis points lower ($t=-5.81$) than all other observations while a complete liquidation at a gain predicts returns 44 basis points lower ($t=-4.03$). This result supports my initial prediction that, due to the disposition effect, realized losses will have more predictive power than realized gains. It is also evidence against a portfolio rebalancing explanation: complete liquidations are unlikely to be driven by rebalancing motives. However, I caution against too strong of an interpretation of my findings as the spread between the predictive power of sales at a loss and the predictive power of sales at a gain narrows significantly when I look at the predictive power for six-month returns.

6 Conclusion

I show that a simple filtering technique allows us to extract information from the trades of informed investors in a much more efficient way. Specifically, I document that a sale of stock at a loss by a company insider is a much more negative signal for future stock returns than a sale of stock by a company insider at a gain. I consider a range of explanations for my results, including investor
heterogeneity, taxes, the short-swing rule, and rebalancing motives, but find that
the evidence is most consistent with the idea that investors derive direct disutility
from selling a stock at a loss. Since selling at a loss is painful, an investor who does
so must have particularly negative information, information that manifests itself
in a poor stock return over the next few months. By comparing the predictive
power of sales of endowed shares at a loss with the predictive power of purchased
shares at a loss, I am able to shed light on the source of this disutility. I find
evidence that selling at a loss is painful because it forces the investor to admit
that an earlier purchase decision was a mistake.
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7 Tables and Figures

I consider a panel of all insider-firm combinations. I include monthly observations for each insider from the month of her first transaction at the firm to the month of her last transaction at the firm. Each 2x2 matrix highlights the disposition effect for insiders. Observations are at the insider-firm-month level. For example, the left matrix shows that there were 298,297 monthly observations where an insider sold at a gain. A stock is considered to be trading at a gain (loss) if the previous month-end price is above (below) the reference price. The left matrix presents the results when the average of the previous six month-end prices is used as the reference point. The right matrix presents the results when the previous purchase price is used as the reference point. I restrict my sample in the right matrix to observations where the insider has a previous purchase price. PGR and PLR refer to the proportion of gains realized and the proportion of losses realized, respectively.

Table 1: Disposition Effect

<table>
<thead>
<tr>
<th></th>
<th>Gain</th>
<th>Loss</th>
<th>Gain</th>
<th>Loss</th>
</tr>
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<tr>
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<td>3,088,356</td>
<td>No Sale</td>
<td>1,379,721</td>
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<tr>
<td>Sale</td>
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<td>119,230</td>
<td>Sale</td>
<td>43,723</td>
</tr>
<tr>
<td>PGR=0.0703</td>
<td>PLR=0.0372</td>
<td></td>
<td>PGR=0.0462</td>
<td>PLR=0.0223</td>
</tr>
</tbody>
</table>
Table 2: Predictive Power of Sales at a Loss for One-Month Returns

The dependent variable is the return from month $t$ to month $t+1$. All buy and sell variables are dummies that equal one if the stated trade occurred in the associated firm-month. The reference price used heads each column. Purchase, Endowed, and Acquisition represent the most recent purchase, endowed, or acquisition price, respectively. WA Purchase (Acquisition) refers to a share-weighted average of previous purchase (acquisition) prices. MA refers to an average of the previous six month-end prices. EA is the experience-average reference point that equals an average of month-end prices based on the tenure of the insider.

I include month fixed effects and cluster standard errors by month. Price Below the Reference Price is (are) dummies that equal one if the previous month-end price is below the reference price(s). Short-Term Reversal equals the return from $t-1$ to $t$ and Momentum equals the return from $t-12$ to $t-1$. Book-to-Market is the log value of common equity divided by market capitalization. CGO (capital gains overhang) is a control that looks at the how the price relates to the average investor’s reference price. I drop all observations where the month-end price is less than one. I multiply all coefficient estimates by 100. The F-statistic tests whether the coefficient on Sale Below Reference Price equals the coefficient on Sale Above Reference Price. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
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<th>Endowed</th>
<th>Acquisition</th>
<th>WA Purchase</th>
<th>WA Acquisition</th>
<th>MA</th>
<th>EA</th>
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</thead>
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<td>-2.34**</td>
<td>-2.36**</td>
<td>-2.37**</td>
<td>-2.36**</td>
<td>-2.35**</td>
<td>-2.36**</td>
<td>-2.35**</td>
<td>-2.11**</td>
</tr>
<tr>
<td>Momentum</td>
<td>0.49**</td>
<td>0.48**</td>
<td>0.48**</td>
<td>0.48**</td>
<td>0.48**</td>
<td>0.48**</td>
<td>0.39*</td>
<td>0.14</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>0.35***</td>
<td>0.36***</td>
<td>0.36***</td>
<td>0.36***</td>
<td>0.36***</td>
<td>0.36***</td>
<td>0.35***</td>
<td>0.35***</td>
</tr>
<tr>
<td>Size</td>
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<td>-0.01</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.01</td>
<td>-0.00</td>
<td>-0.01</td>
<td>-0.02</td>
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<td>Buy</td>
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<td>0.79***</td>
<td>0.78***</td>
<td>0.78***</td>
<td>0.79***</td>
<td>0.78***</td>
<td>0.81***</td>
<td>0.81***</td>
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<tr>
<td>Sale</td>
<td>-0.17**</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Sale Below Reference Price</td>
<td>-0.72***</td>
<td>-0.31***</td>
<td>-0.31***</td>
<td>-0.74***</td>
<td>-0.46***</td>
<td>-0.59***</td>
<td>-0.64***</td>
<td></td>
</tr>
<tr>
<td>Sale Above Reference Price</td>
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<td>0.02</td>
<td>-0.02</td>
<td>-0.10</td>
<td>-0.04</td>
<td>-0.01</td>
<td>-0.11</td>
<td></td>
</tr>
<tr>
<td>CGO</td>
<td>-1.30***</td>
<td>-1.30***</td>
<td>-1.30***</td>
<td>-1.30***</td>
<td>-1.30***</td>
<td>-1.30***</td>
<td>-1.37***</td>
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<td>Price Below Reference Price</td>
<td>N</td>
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<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>F-statistic</td>
<td>11.56***</td>
<td>6.53**</td>
<td>5.52**</td>
<td>12.01***</td>
<td>7.02***</td>
<td>25.39***</td>
<td>20.43***</td>
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</tr>
</tbody>
</table>

$N$ statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Table 3: Portfolio Returns

At the beginning of each month I construct long-short portfolios; this table shows the monthly alphas in percentage terms. I drop all observations where the month-end price is less than one dollar. RLPur (RGPur) represents a realized loss (gain) relative to the previous purchase price. RLMA (RGMA) indicates a realized loss (gain) relative to the six-month moving average. For example, Buy-RLMA corresponds to a portfolio that goes long a firm if one of its insider bought shares in the previous month and short a firm if one of its insiders sold shares below the six-month moving average. I put t-statistics in parentheses. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

### Equal-Weighted Portfolios

<table>
<thead>
<tr>
<th>Buy-Sale</th>
<th>Buy-RLPur</th>
<th>Buy-RGPur</th>
<th>Buy-RLMA</th>
<th>Buy-RGMA</th>
<th>RGPur-RLPur</th>
<th>RGMA-RLMA</th>
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</thead>
<tbody>
<tr>
<td>Raw Return</td>
<td>1.02***</td>
<td>1.60***</td>
<td>1.07***</td>
<td>1.63***</td>
<td>0.90***</td>
<td>0.60***</td>
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<tr>
<td></td>
<td>(8.71)</td>
<td>(9.57)</td>
<td>(6.02)</td>
<td>(11.20)</td>
<td>(5.74)</td>
<td>(2.81)</td>
</tr>
<tr>
<td>Three-Factor Alpha</td>
<td>0.94***</td>
<td>1.61***</td>
<td>0.96***</td>
<td>1.57***</td>
<td>0.80***</td>
<td>0.71***</td>
</tr>
<tr>
<td></td>
<td>(8.00)</td>
<td>(9.47)</td>
<td>(5.40)</td>
<td>(10.67)</td>
<td>(5.04)</td>
<td>(3.33)</td>
</tr>
<tr>
<td>Four-Factor Alpha</td>
<td>0.94***</td>
<td>1.65***</td>
<td>0.93***</td>
<td>1.57***</td>
<td>0.79***</td>
<td>0.77***</td>
</tr>
<tr>
<td></td>
<td>(7.89)</td>
<td>(9.54)</td>
<td>(5.16)</td>
<td>(10.53)</td>
<td>(4.92)</td>
<td>(3.56)</td>
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### Value-Weighted Portfolios

<table>
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<th>Buy-RGPur</th>
<th>Buy-RLMA</th>
<th>Buy-RGMA</th>
<th>RGPur-RLPur</th>
<th>RGMA-RLMA</th>
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<tbody>
<tr>
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<td>0.43***</td>
<td>1.00***</td>
<td>0.45***</td>
<td>0.69***</td>
<td>0.41***</td>
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<tr>
<td></td>
<td>(3.26)</td>
<td>(4.16)</td>
<td>(2.65)</td>
<td>(3.72)</td>
<td>(2.81)</td>
<td>(2.27)</td>
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<tr>
<td>Three-Factor Alpha</td>
<td>0.41***</td>
<td>1.06***</td>
<td>0.46***</td>
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<td>0.43***</td>
<td>0.67**</td>
</tr>
<tr>
<td></td>
<td>(3.13)</td>
<td>(4.33)</td>
<td>(2.69)</td>
<td>(3.51)</td>
<td>(2.94)</td>
<td>(2.41)</td>
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<tr>
<td>Four-Factor Alpha</td>
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<td>1.08***</td>
<td>0.42***</td>
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<td>(4.36)</td>
<td>(2.46)</td>
<td>(3.38)</td>
<td>(2.79)</td>
<td>(2.59)</td>
</tr>
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</table>
Table 4: Predictive Power of Sales at a Loss for Six-Month Returns

The dependent variable in these regressions is the future six-month return (t, t+6). The reference price used is labeled at the top of each column. The MA reference price is the average of the previous six month-end prices. Purchase refers to the previous purchase price. Short-Term Reversal equals the return from \( t - 1 \) to \( t \) and Momentum equals the return from \( t - 12 \) to \( t - 1 \). Book-to-Market is the log value of common equity divided by market capitalization. Size is the log value of market capitalization. CGO (capital gains overhang) is a control that looks at how the price relates to the average investor’s reference price. Price Below MA is a dummy variable that equals one if the previous month-end price was below the six-month moving average. I include month-fixed effects and cluster standard errors by month. I drop all observations where the month-end price is less than one. I multiply all coefficient estimates by 100. The F-statistic tests whether the coefficient on Sale Below Reference Price equals the coefficient on Sale Above Reference Price. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
<thead>
<tr>
<th>MA Reference Price</th>
<th>Purchase Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short-Term Reversal</td>
<td>4.78** (2.09)</td>
</tr>
<tr>
<td>Momentum</td>
<td>1.25** (2.43)</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>0.94** (2.28)</td>
</tr>
<tr>
<td>Size</td>
<td>-0.21 (-1.53)</td>
</tr>
<tr>
<td>Buy</td>
<td>1.62*** (6.98)</td>
</tr>
<tr>
<td>Sale Below Reference Price</td>
<td>-1.81*** (-7.51)</td>
</tr>
<tr>
<td>Sale Above Reference Price</td>
<td>0.10 (0.54)</td>
</tr>
<tr>
<td>CGO</td>
<td>-6.09*** (-4.40)</td>
</tr>
<tr>
<td>Price Below MA</td>
<td>-3.73*** (-9.03)</td>
</tr>
<tr>
<td>F-statistic</td>
<td>36.80***</td>
</tr>
<tr>
<td>N</td>
<td>584037 584098</td>
</tr>
</tbody>
</table>

\( t \) statistics in parentheses

* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)
Table 5: Size of the Gain or Loss

The future one-month return is the dependent variable in the first column and the future six-month return is the dependent variable in the second column. I include month fixed effects and cluster standard errors by month. The buy and sell variables are dummies that take a value of one in a specific firm-month if one of the firm’s insiders made the associated purchase or sale in that month. I use the six-month moving average, or the average of the previous six month-end prices, as the reference price. I separate large gains (losses) from small gains (losses) using a divider twenty percent above (below) the moving average. I create three price dummies, each associated with one of three sub-regions (I exclude one), that equal one if the previous month-end price falls into the specified region. CGO (capital gains overhang) is a control that looks at how the price relates to the average investor’s reference price. I include additional controls for the short-term reversal anomaly, the momentum anomaly, the value anomaly, and the size anomaly. I multiply all coefficient estimates by 100. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
<thead>
<tr>
<th></th>
<th>One Month Return</th>
<th>Six Month Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy</td>
<td>0.81***</td>
<td>1.68***</td>
</tr>
<tr>
<td></td>
<td>(9.57)</td>
<td>(7.21)</td>
</tr>
<tr>
<td>Sale at Large Gain</td>
<td>0.27*</td>
<td>0.22</td>
</tr>
<tr>
<td></td>
<td>(1.93)</td>
<td>(0.54)</td>
</tr>
<tr>
<td>Sale at Small Gain</td>
<td>-0.14**</td>
<td>-0.21***</td>
</tr>
<tr>
<td></td>
<td>(-2.08)</td>
<td>(-3.00)</td>
</tr>
<tr>
<td>Sale at Small Loss</td>
<td>-0.51***</td>
<td>-1.64***</td>
</tr>
<tr>
<td></td>
<td>(-6.97)</td>
<td>(-7.75)</td>
</tr>
<tr>
<td>Sale at Large Loss</td>
<td>-0.70***</td>
<td>-2.08***</td>
</tr>
<tr>
<td></td>
<td>(-3.00)</td>
<td>(-3.42)</td>
</tr>
<tr>
<td>CGO</td>
<td>-1.30***</td>
<td>-6.27***</td>
</tr>
<tr>
<td></td>
<td>(-3.95)</td>
<td>(-4.76)</td>
</tr>
<tr>
<td>N</td>
<td>590210</td>
<td>584037</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Table 6: Individual-Level Analysis

I consider a panel of all insider-firm combinations. I include monthly observations for each insider from the month of her first transaction at the firm to the month of her last transaction at the firm. The first three columns limit the sample to insider-firm-month observations where the insider made a sale. The second column further limits the sample to insider-firm-months with a sale by the CFO. The moving average is the average of the previous six month-end prices. A purchaser is an insider who has made an open market purchase. The dependent variable in the first three columns is the future 1-month return (t, t+1). I include insider-firm and month fixed effects and cluster standard errors by month. In the first three columns, I include controls for capital gains overhang, the short-term reversal anomaly, the momentum anomaly, the value anomaly, and the size anomaly. The last column limits the sample to insider-firm-month observations where the insider historically made a purchase and historically received shares. The dependent variable is a dummy variable that equals one if there was a sale by the insider in the associated month and firm. I cluster standard errors by firm-month and include firm-month fixed effects. The endowed (purchase) price refers to the most recent price at which the insider was given (purchased) shares. I multiply all coefficient estimates by 100. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
<thead>
<tr>
<th></th>
<th>One Month Return</th>
<th>One Month Return</th>
<th>One Month Return</th>
<th>Sale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sale Below Moving Average</td>
<td>-0.57***</td>
<td>0.05</td>
<td>-0.46**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.31)</td>
<td>(0.15)</td>
<td>(-2.47)</td>
<td></td>
</tr>
<tr>
<td>Sale Below Moving Average by Purchaser</td>
<td></td>
<td></td>
<td>-0.35**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(-2.11)</td>
<td></td>
</tr>
<tr>
<td>Price Below Purchase Price</td>
<td>-0.29***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-5.65)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price Below Endowed Price</td>
<td>0.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>10.00***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td>N</td>
<td>312843</td>
<td>19070</td>
<td>312843</td>
<td>1703926</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
I consider a sample of firm-months since 1989. The dependent variable in these panel regressions is the future 1-month return \((t, t+1)\). I classify insiders who have traded for three consecutive years. An insider is labeled routine if she made a trade in the same month for three consecutive years. All remaining insiders are classified as opportunistic. Dummies for opportunistic (routine) buys and sales take a value of one for a specific firm, month entry if a firm’s opportunistic (routine) insider bought or sold, respectively, in that month. Short-Term Reversal equals the return from \(t-1\) to \(t\) and Momentum equals the return from \(t-12\) to \(t-1\). Book-to-Market is the log value of common equity divided by market capitalization. Size is the log value of market capitalization. CGO (capital gains overhang) is a control that looks at how the price relates to the average investor’s reference price. I include month fixed effects. Standard errors are clustered by month. MA (“moving average”) is the reference price, and is equal to the average of the previous six month-end prices. Below MA is a dummy that equals one if the previous month-end price is below the moving-average. I multiply all coefficient estimates by 100. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-statistic</th>
</tr>
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<tbody>
<tr>
<td>Short-Term Reversal</td>
<td>-2.95***</td>
<td>(-3.02)</td>
<td>(-3.02)</td>
</tr>
<tr>
<td></td>
<td>-2.23**</td>
<td>(-2.19)</td>
<td>(-2.19)</td>
</tr>
<tr>
<td></td>
<td>-2.24**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Momentum</td>
<td>0.367*</td>
<td>(1.81)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.512**</td>
<td>(2.50)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.513***</td>
<td>(2.50)</td>
<td></td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>0.459***</td>
<td>(4.17)</td>
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</tr>
<tr>
<td></td>
<td>0.267**</td>
<td>(2.38)</td>
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</tr>
<tr>
<td></td>
<td>0.264***</td>
<td>(2.35)</td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>-0.132***</td>
<td>(-2.88)</td>
<td>(-2.88)</td>
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<tr>
<td></td>
<td>-0.0479</td>
<td>(-1.05)</td>
<td>(-1.05)</td>
</tr>
<tr>
<td></td>
<td>-0.0452</td>
<td>(-0.99)</td>
<td>(-0.99)</td>
</tr>
<tr>
<td>Opportunistic Buy</td>
<td>0.538***</td>
<td>(4.04)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.482**</td>
<td>(3.28)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.493***</td>
<td>(3.35)</td>
<td></td>
</tr>
<tr>
<td>Routine Buy</td>
<td>-0.12</td>
<td>(-0.64)</td>
<td>(-0.64)</td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>(0.06)</td>
<td>(0.06)</td>
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<tr>
<td></td>
<td>0.01</td>
<td>(0.04)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Opportunistic Sale</td>
<td>-0.22***</td>
<td>(-2.91)</td>
<td></td>
</tr>
<tr>
<td>Routine Sale</td>
<td>0.00</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>Routine Sale Below MA</td>
<td>-0.15</td>
<td>(-1.04)</td>
<td>(-1.04)</td>
</tr>
<tr>
<td>Routine Sale Above MA</td>
<td>-0.08</td>
<td>(-0.66)</td>
<td>(-0.66)</td>
</tr>
<tr>
<td>Opportunistic Sale Below MA</td>
<td>-0.51***</td>
<td>(-3.97)</td>
<td></td>
</tr>
<tr>
<td>Opportunistic Sale Above MA</td>
<td>-0.12</td>
<td>(-1.31)</td>
<td>(-1.31)</td>
</tr>
<tr>
<td>Below MA</td>
<td>-0.48***</td>
<td>(-3.23)</td>
<td>(-3.23)</td>
</tr>
<tr>
<td></td>
<td>-0.47***</td>
<td>(-3.19)</td>
<td></td>
</tr>
<tr>
<td>CGO</td>
<td>-1.52***</td>
<td>(-3.80)</td>
<td>(-3.80)</td>
</tr>
<tr>
<td></td>
<td>-1.52***</td>
<td>(-3.80)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>4.35***</td>
<td>(4.97)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.57***</td>
<td>(2.87)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2.52***</td>
<td>(2.83)</td>
<td></td>
</tr>
</tbody>
</table>

\(N\) = 687789  
\(t\) statistics in parentheses.  
* \(p < 0.10\), ** \(p < 0.05\), *** \(p < 0.01\)

49
Table 8: Purchases Above and Below the Reference Price

The dependent variable is the future one-month return (t, t+1) in the first two columns and the future six-month return in the last two columns. The reference price used is at the top of each column. MA is the average of the previous six month-end prices. CGO (capital gains overhang) is a control that looks at how the price relates to the average investor’s reference price. In regressions where I use variables associated with the MA reference price, I include a dummy variable that equals one if the previous month-end price was below the reference price. I include additional controls for the short-term reversal anomaly, the momentum anomaly, the value anomaly, and the size anomaly. I multiply all coefficient estimates by 100. The F-statistic tests whether the coefficient on a purchase below the reference price equals the coefficient on a purchase above the reference price. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
<thead>
<tr>
<th></th>
<th>MA</th>
<th>Purchase</th>
<th>MA</th>
<th>Purchase</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy Above Reference Price</td>
<td>0.71***</td>
<td>0.75***</td>
<td>2.56***</td>
<td>2.15***</td>
</tr>
<tr>
<td></td>
<td>(7.03)</td>
<td>(8.49)</td>
<td>(9.44)</td>
<td>(8.79)</td>
</tr>
<tr>
<td>Buy Below Reference Price</td>
<td>0.76***</td>
<td>0.44***</td>
<td>0.69**</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(6.33)</td>
<td>(3.52)</td>
<td>(2.25)</td>
<td>(-0.32)</td>
</tr>
<tr>
<td>Sale Below Reference Price</td>
<td>-0.59***</td>
<td>-0.71***</td>
<td>-1.76***</td>
<td>-2.32***</td>
</tr>
<tr>
<td></td>
<td>(-6.94)</td>
<td>(-4.56)</td>
<td>(-7.30)</td>
<td>(-4.98)</td>
</tr>
<tr>
<td>Sale Above Reference Price</td>
<td>-0.01</td>
<td>-0.08</td>
<td>0.05</td>
<td>-0.15</td>
</tr>
<tr>
<td></td>
<td>(-0.14)</td>
<td>(-1.10)</td>
<td>(0.29)</td>
<td>(-0.70)</td>
</tr>
<tr>
<td>CGO</td>
<td>-1.37***</td>
<td>-1.31***</td>
<td>-6.11***</td>
<td>-5.68***</td>
</tr>
<tr>
<td></td>
<td>(-3.76)</td>
<td>(-3.59)</td>
<td>(-4.41)</td>
<td>(-4.09)</td>
</tr>
<tr>
<td>Price Below MA</td>
<td>-0.53***</td>
<td>-3.60***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.67)</td>
<td>(-8.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td>0.09</td>
<td>4.02**</td>
<td>20.32***</td>
<td>23.63***</td>
</tr>
</tbody>
</table>

N 590210  590272  584037  584098

* p < 0.10, ** p < 0.05, *** p < 0.01

t statistics in parentheses
Table 9: Mutual Fund Regressions

The future one-month return is the dependent variable. I use a weighted-average of purchase prices as the reference price. I use FIFO (first in, first out) accounting to determine which shares are currently held. Sold at Loss is a dummy that equals one if the stock was sold at a loss. Sold All at Loss equals one if there was a complete liquidation at a loss. Short-Term Reversal equals the return from $t-1$ to $t$ and Momentum equals the return from $t-12$ to $t-1$. Book-to-Market is the log value of common equity divided by market capitalization. Size is the log value of market capitalization. CGO (capital gains overhang) is a control that looks at how the price relates to the average investor’s reference price. I include a dummy variable(s) that equals one if the previous month-end price was below the reference price. I include month and fund fixed effects. I multiply all coefficient estimates by 100. Standard errors are clustered by month. * indicates significance at the ten percent level, ** indicates significance at the five percent level, and *** stars indicates significance at the one-percent level.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short-Term Reversal</td>
<td>-2.72</td>
<td>-2.84</td>
</tr>
<tr>
<td></td>
<td>(-1.37)</td>
<td>(-1.43)</td>
</tr>
<tr>
<td>Momentum</td>
<td>-0.00</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>(-0.00)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Book-to-Market</td>
<td>0.31**</td>
<td>0.30**</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(1.98)</td>
</tr>
<tr>
<td>Size</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.18)</td>
</tr>
<tr>
<td>Sold at Loss</td>
<td>-0.33***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-3.13)</td>
<td></td>
</tr>
<tr>
<td>Sold at Gain</td>
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<td></td>
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<tr>
<td></td>
<td>(-1.45)</td>
<td></td>
</tr>
<tr>
<td>Sold All at Loss</td>
<td></td>
<td>-1.59***</td>
</tr>
<tr>
<td></td>
<td></td>
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<tr>
<td>Sold All at Gain</td>
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<td></td>
<td></td>
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<td>Price Below Reference Point</td>
<td>-0.35**</td>
<td>-0.26</td>
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<tr>
<td></td>
<td>(-2.32)</td>
<td>(-1.43)</td>
</tr>
<tr>
<td>CGO</td>
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<td>-2.50***</td>
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<td>(-2.85)</td>
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<tr>
<td>N</td>
<td>12987485</td>
<td>12987485</td>
</tr>
</tbody>
</table>

$ t $ statistics in parentheses

* $ p < 0.10 $, ** $ p < 0.05 $, *** $ p < 0.01 $
This graph plots the coefficients on the dummy variables “Sale Below Purchase Price” and “Sale Above Purchase Price” from estimating

\[
\text{Return}_{i,t \rightarrow t+j} = \beta_0 + \beta_1 \text{Short-Term Reversal}_{i,t} + \beta_2 \text{Momentum}_{i,t} + \beta_3 \text{Book-to-Market}_{i,t} \\
+ \beta_4 \text{Size}_{i,t} + \beta_5 \text{Buy}_{i,t} + \beta_6 \text{Sale Below Purchase Price}_{i,t} + \\
\beta_7 \text{Sale Above Purchase Price}_{i,t} + \beta_8 \text{Capital Gains Overhang}_{i,t} + \gamma \text{Month} + \epsilon_{i,t}
\]

over different return horizons \( j \). The x-axis displays the time horizon, in months, over which returns are predicted. The y-axis displays the expected percentage difference in returns when the dummy variable equals one compared to when the dummy variable equals zero.