Do Investors Integrate Losses and Segregate Gains? Mental Accounting and Investor Trading Decisions

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Using trading records of individual investors at a large discount brokerage firm, this paper tests whether investors' trading decisions are influenced by their preferences for framing gains and losses. I find that investors are more likely to bundle sales of losers on the same day than sales of winners. This result is consistent with the implication of mental accounting principles (Thaler (1985)), according to which individuals attain higher utility by integrating losses and segregating gains. Alternative explanations based on tax-loss selling strategies, margin calls, the number of stocks in the portfolio, the difference in the potential proceeds from selling winners and losers, correlations among winners and among losers in a portfolio, and potential delays in sales order execution do not fully account for the observed behavior. Logistic analyses show that investors are more likely to sell multiple stocks when they realize losses, after controlling for various factors including market and portfolio returns, overall sales activity during the day, and investor characteristics.

1 Introduction

Recently, researchers have argued that prospect theory (Kahneman and Tversky (1979)) and mental accounting (Thaler (1985)) provide possible explanations for investor behavior (e.g., the disposition effect[1]) and for outstanding asset pricing anomalies such as the equity premium puzzle, the value premium, and the momentum effect.[2] In this paper, I test the effect of mental accounting and prospect theory on actual investor trading decisions in stock markets. This provides more direct insight into whether mental accounting and prospect theory are likely explanations for capital market anomalies.

In prospect theory, individuals evaluate outcomes using an "S"-shaped value function. The value function is defined over gains and losses and shows diminishing sensitivity to both gains and losses. Mental accounting concerns the way investors evaluate outcomes using the value function. For example, whether investors evaluate the overall outcome or evaluate each outcome separately is a question of mental accounting. Diminishing sensitivity of the value function implies that individuals attain higher utility by evaluating losses together and gains separately. If investors try to evaluate outcomes in whatever way makes them happiest, they prefer integrating losses and segregating gains (the hedonic editing hypothesis; Thaler (1985)).

Choices over the timing of events are likely to reflect preferences for integrating or segregating outcomes (e.g., Thaler and Johnson (1990)): Integration is easier if events occur on the same day and segregation is easier if events occur on different days. If so, people prefer to have events occur on the same day if integration is desired. Similarly, people prefer to have events occur on different days if segregation is desired. When investors sell stocks, they choose whether to realize gains and losses together or separately. Therefore, stock sales by investors provide a natural setting to test the hedonic editing hypothesis. We can infer investors' preferences for framing gains and losses by examining how they time the gains and losses from stocks sales.

[1] E.g., Shefrin and Statman (1985), Ferris, Haugen, and Makhija (1988), Odean (1998), Locke and Mann (2000), Weber and Camerer (2000), Genesove and Mayer (2001), Grinblatt and Keloharju (2001a), Shapira and Venezia (2001), Dhar and Zhu (2002).

[2] E.g., Benartzi and Thaler (1995), Barberis, Huang, and Santos (2001), Barberis and Huang (2001), Grinblatt and Han (2002).

Using the trading records of individual investors at a large discount brokerage house during 1991-1996, I document that investors are more likely to bundle sales of stocks that are trading below their purchase prices ("losers") on the same day than sales of stocks that are trading above their purchase prices ("winners"). Selling losers on the same day makes it easier for investors to aggregate their losses, and selling winners on different days makes it easier to segregate their gains. Therefore, investors' selling behavior observed in this study can be interpreted as a consequence of their preferences for mentally aggregating and segregating events, preferences that are driven by their desire to perceive outcomes in more favorable ways.

In testing the hedonic editing hypothesis, it is important to consider possible alternative explanations for why losers are more likely to be sold on the same day than winners. Tax-loss selling strategies implemented near the end of the year, for example, may induce clustering of loss selling. Margin calls can trigger sales of multiple stocks that are likely to be losers. Investors might simply have more losers than winners in their portfolios, increasing the chance of selling multiple losers than of selling multiple winners. Since the dollar value of a loser is probably smaller than the dollar value of a winner, an investor who has a fixed proceeds target may need to sell multiple losers while selling one winner would suffice. Losers in a portfolio might be more correlated with each other than winners and therefore more likely to be sold together due to greater commonality. Good-till-cancel limit orders may take longer than a day to be executed, and investors' greater use of limit orders for winners than losers can spread out sales of winners than sales of losers. I examine these alternative hypotheses in univariate tests and also in multivariate tests. Some of the alternative stories provide a significant explanatory power but do not fully account for investors' tendency to realize multiple losses than gains on the same day.

As an alternative testing approach, the probability of multiple stock sales is modeled under the assumption that the selling decision of each stock is independent. Under this assumption, the probability of multiple stock sales increases with the number of winners and with the number of losers in the portfolio, and the impact of an additional winner (loser) on the probability of multiple stock sales increases with the investor's propensity to sell a winner (loser). Studies have documented that investors' propensity to sell a winner is greater than their propensity to sell a loser (the disposition effect). Thus, the impact of an additional winner on the probability of multiple stock sales should be larger than that of an additional loser if selling decisions are independent. However, the result shows that the effect of an additional loser on the probability of multiple stock sales is much larger than the effect of an additional winner, opposite of what is expected when sales decisions are independent and investors show disposition effect. Thus, this evidence suggests that selling decisions of losers are more positively correlated than selling decisions of winners.

The contributions of this paper can be summarized as follows. First, it develops a hypothesis on investor trading behavior from the principles of mental accounting (Thaler (1985)) and provides evidence that investors' stock selling decisions are consistent with the implications of prospect theory and mental accounting. A growing body of theoretical models are based on assumptions derived from psychological findings. However, "it is often not obvious how to translate preexisting evidence from psychological experiments into assumptions about investors in real financial settings. (Hirshleifer (2001), p. 1577)" This study tries to fill this gap by developing and testing a prediction from psychological theories on the actual behavior of market participants.

Second, it complements recent studies on individual investor trading decisions, most of which have examined the trading decisions for each stock separately.[3] In contrast, this paper examines how selling decisions on multiple stocks interact with each other, even in the absence of common fundamental factors.

Finally, the empirical finding of this paper may have further implications on the study of equilibrium stock prices. Investors' asymmetric selling decisions for their winners and losers can contribute to the asymmetry in the stock market. For example, empirical evidence shows that correlations of stock returns are higher in down markets than in up markets.[4] Higher

[3]E.g., Odean (1998), Odean (1999), Barber and Odean (2000), Barber and Odean (2001), Barber and Odean (2002), Grinblatt and Keloharju (2001b), Grinblatt and Keloharju (2001a), Dhar and Kumar (2002), Hirshleifer, Myers, Myers, and Teoh (2002), Hong and Kumar (2002), Kumar (2002), and Zhu (2002).

[4]E.g., Longin and Solnik (2001), Ang and Chen (2002).

correlations of stock returns in down markets could be due to greater correlations in selling decisions on losers.[5] In addition, investors' selective adoption of different mental accounting systems may affect asset prices. Barberis and Huang (2001) consider two forms of mental accounting, one in which investors care about the gains and losses in the value of individual stocks (individual stock accounting) and the other in which investors care about the gains and losses in the value of the overall portfolio (portfolio accounting), and show that the form of mental accounting affects asset prices in a significant way. If investors prefer integrating their losses and segregating their gains, as the results of this paper suggest, portfolio accounting (individual stock accounting) will be more prevalent in a down (up) market, implying different market behavior in up and down markets.

The remainder of the paper is organized as follows. Section 2 reviews the literature on prospect theory and mental accounting. Section 3 lists the hypotheses to be tested, and Section 4 describes the data and the empirical results. Section 5 discusses further implications of mental accounting principles, and Section 6 concludes the paper.

2 Literature Review

2.1 Prospect Theory and Mental Accounting

Kahneman and Tversky (1979) propose prospect theory as a descriptive model of decision making. In prospect theory, individuals maximize over a value function instead of the standard utility function. The value function is defined over gains and losses relative to a reference point rather than over levels of wealth. The function is concave for gains, convex for losses, and steeper for losses than for gains.

The prospect theory value function is defined over single outcomes. Then, a question arises as to how to use the value function to evaluate multiple outcomes: Do people evaluate the aggregated outcomes or do they evaluate each outcome separately? This question is related to mental accounting (Thaler (1985)), which refers to the way investors frame their financial decisions and evaluate the outcomes of their investments.

[5] Kyle and Xiong (2001) show that simultaneous liquidation of unrelated securities due to wealth effects can lead to financial contagion.

Thaler (1985) hypothesizes that people try to code outcomes to make themselves as happy as possible (the hedonic editing hypothesis). The hedonic editing hypothesis characterizes decision makers as value maximizers who mentally segregate or integrate outcomes depending on which mental representation is more desirable. For a joint outcome, (x, y), people try to integrate outcomes when integrated evaluation yields higher value than separate evaluations, $v(x+y) > v(x)+v(y)$, and try to segregate outcomes when segregation yields higher value, $v(x+y) < v(x) + v(y)$. Under this assumption, Thaler (1985) derives mental accounting principles that determine whether segregation or integration is preferred. The principles indicates that individuals should segregate gains and integrate losses because the value function exhibits diminishing sensitivity as the magnitude of a gain or a loss becomes greater (Figures 1 and 2). Individuals can maximize their happiness by savoring gains one by one, while minimizing the pain by thinking about the overall loss rather than individual losses. For mixed outcomes, whether or not integration is preferred to segregation depends on the relative magnitudes of the gain and the loss. Since a loss hurts more than a gain of the same amount (loss-aversion), it is better to combine a loss with a larger gain than to segregate them. Diminishing sensitivity of the value function implies that it is preferred to segregate a small gain as a "silver lining" than to combine it with a large loss.

2.2 Test of the Hedonic Editing Hypothesis

In principle, individuals could divide or combine gains and losses completely arbitrarily in order to maximize their happiness. However, there are limits to the degree to which people can mentally segregate and integrate outcomes. Thaler and Johnson (1990) propose that temporal separation of events facilitates segregation of outcomes and temporal proximity facilitates integration. If so, the hedonic editing rules imply that people prefer to experience events on different days when segregation is preferred, and on the same day when integration is desired. Thus, we can test whether people engage in "hedonic editing" by looking at their choices over the timing of events.

There are relatively few papers that test the hedonic editing hypothesis. For mixed outcomes, Linville and Fischer (1991) find that people prefer to have a negative event with an offsetting positive event on the same days. Hirst, Joyce, and Schadewald (1994) find that people prefer to finance purchases of goods with loans whose terms correspond with the life of the good. As consumer purchases are voluntary, the costs of the good (losses) are likely to be smaller than its benefits (gains). Therefore, these results provide supporting evidence for the mental accounting principle that people prefer to combine a loss with a larger gain. For multiple gains and multiple losses, Thaler and Johnson (1990) and Linville and Fischer (1991) find that people prefer to have positive events and also negative events on different days, providing only mixed support for the hypothesis. Although people think aggregated losses are better than segregated ones (Thaler (1985)), they seem to be have difficulty in adding one loss to another on the same day. Linville and Fischer (1991) suggest that people have resources that are limited but renewable over time (e.g., after a good night's sleep) for dealing with emotionally impactful events. If other factors such as limited daily gain-savoring and loss-buffering resources are also important determinants of the preferences for experiencing events on the same day or different days, a relative comparison of the preferences for combining gains and the preferences for combining losses can help isolate the effect of mental accounting on the choice of temporally separating or combining multiple gains or losses. Also, these studies are based on responses to questions about hypothetical alternatives, not on the behavior of investors faced with actual investment choices. In this study, I examine preferences for integrating and segregating outcomes as exhibited in actual trading decisions of individual investors and try to minimize the effects of other determinants of trade timing decisions by comparing investors' tendency to aggregate losses with their tendency to aggregate gains.

One may argue that a price drop is economically the same negative event regardless of whether the investor sells the stock or keeps it. However, people seem to perceive paper losses and realized losses differently, with the latter being taken more seriously.[6] So long as the stock remains in the portfolio, investors can still hope that it will rebound in the future. However, selling a stock makes the outcome seem irreversible. In addition, selling the stock at a loss

[6]When Sam Walton lost $1.7 billion during the great stock market crash of October 19, 1987, he responded "It's paper anyway"(Ortega (1998)).

forces investors to admit that they have made mistakes in the past, which is a painful thing to do (Shefrin and Statman (1985)). As long as it is painful to sell a stock at a loss, the pain will be minimized by selling losers at the same time according to the principles of mental accounting. Similarly, selling a stock at a gain will be registered as a positive event, so people will prefer selling winners on different days to maximize their happiness.

3 Hypotheses

The hedonic editing hypothesis implies that investors prefer to sell losers than winners on the same day. Therefore the main hypothesis of this paper is posited as follows:

Hypothesis: *Investors' propensity to sell multiple stocks on the same day is greater when they realize losses than when they realize gains.*

There are several alternative explanations for why investors may sell multiple losers on the same day more often than multiple winners.

- **Tax-loss selling**: It is well known that tax-loss selling is concentrated at the end of the year.[7] If investors sell disproportionately more losers near the end of year for tax reasons, they may sell multiple losers on the same day.

- **Margin calls**: Margin calls force investors to liquidate their positions in some stocks, possibly leading to multiple stock sales. Since margin calls are triggered by stock price drops, disproportionately more losers than winners will be sold from margin calls. Therefore, margin calls may contribute to the bundling of the sales of losers because such calls tend to result in sales of losers rather than sales of winners.

- **More losers than winners in the portfolio**: The number of stocks that an investor sells largely depends on his/her opportunity to do so, in other words, on the number of stocks the investor currently holds. Investors with a large number of stocks are more likely to sell multiple stocks on the same day than those who have only a few stocks in

[7]Evidence for tax-loss selling near the end of the year can also be found in, for example, Lakonishok and Smidt (1986), Ritter (1988), Badrinath and Lewellen (1991), Odean (1998), and Poterba and Weisbenner (2001).

their portfolios. Thus, the probability of selling multiple losers will be higher than that of selling multiple winners if investors have more losers than winners in their portfolios.

- **Difference in the preference for selling multiple stocks across investors**: It is possible that a certain group of investors always prefers selling multiple stocks per day, regardless of whether the stocks are winners or losers. If those investors happen to have mostly losers rather than winners, investor characteristics, not investors' differential attitudes toward gains and losses, may drive the asymmetric pattern.

- **Smaller proceeds from losers than from winners**: The dollar value of a loser is likely to be smaller than the dollar value of a winner, since losers are those that have fallen in price. This implies that the proceeds from selling a loser are likely to be smaller than the proceeds from selling a winner. If an investor seeks to achieve fixed proceeds from stock sales on a given day, he may need to sell multiple losers whereas selling one winner may suffice.

- **Higher correlation among losers than among winners**: Losers in each investor's portfolio might be more related with each other than winners; therefore they are more likely to be sold together due to news or events that affect them at the same time. If stock return correlations of losers are greater than those of winners, or if losers are more likely than winners to be from similar industries, investors are more likely to sell multiple losers on the same day more often than multiple winners due to the greater commonality of losers.

- **Delays in order execution**: Good-till-cancel limit orders may take longer than a day to be executed if investors do not cancel unexecuted ones at the end of the day.[8] Linnainmaa (2003) presents evidence that investors are more likely to use limit orders when they realize gains than losses. If delays in order execution are more likely when investors realize gains than losses, it is possible to observe the sales of multiple winners over

[8]In the sample of Harris and Hasbrouck (1996), about 82% of limit orders are day orders which are automatically cancelled if not executed until the close, and 17% of limit orders are good-till-cancel orders.

different days than those of losers even though there is no difference between winnenrs and losers in investors' propensity to submit multiple sell orders on the same day.

In order to examine the main hypothesis that mental accounting of multiple outcomes influences the way investors sell stocks, it is important to control for these alternative explanations in the tests. The next section describes the data and presents empirical tests that are designed to address the alternative explanations.

4 Empirical Tests

4.1 Data Description

The data set of individual investor trades used in this study is from a large U.S. discount brokerage house. It contains the daily trading records of 158,034 accounts (78,000 households) from January 1991 to November 1996. The file has more than three million records of trades in common stocks, bonds, mutual funds, American Depositary Receipts (ADRs), etc. Each record has an account identifier, the trade date, an internal security identifier and CUSIP, a buy-sell indicator, the quantity traded, the commission paid, and the price at which the stocks are sold or bought.

The brokerage house labels households with more than $100,000 in equity at any point in time as "Affluent", households that executed more than 48 trades in any year as active "Traders", and the rest as "General". If a household qualifies as active Trader and Affluent, it is considered an active trader. There are a total of 158,034 accounts that are cash, margin, or IRA/Keogh type.

Only trades in common stocks are examined in this study. All trade records are adjusted for stock splits and stock dividends using the Center for Research in Security Prices (CRSP) event files. Multiple trades of the same stock from the same account on the same day are aggregated.

Following previous studies (e.g., Odean (1998) and Grinblatt and Keloharju (2000)), I use the average purchase price as a reference point. When there are multiple purchases preceding a sale, the average purchase price is calculated as a split-adjusted share volume-weighted average.

When a stock is sold, it is considered a winner if the sales price is greater than the average purchase price and a loser otherwise. A stock that remains in the portfolio is also coded as a winner or a loser by comparing the closing stock price on that day with the average purchase price.[9] Sales records are discarded if there is no matching purchase record, since it is not possible to tell whether the sales are at losses or gains. As a consequence, sales of stocks that were purchased prior to January 1991 are not included in this study. Also, observations are dropped if the entire portfolio of stocks is liquidated, because the investor could be closing the account or selling all stocks in the portfolio because of liquidity needs.

Table 1 describes the sample of investor trades used in this study. Sales records from a total of 50,229 accounts are examined. Of these accounts, 17.2 percent are cash accounts, 49 percent are margin accounts, and 33.8 percent are IRA/Keogh accounts. The majority of accounts belong to general households (59.4 percent), and affluent and trader households account for 18.3 percent and 22.3 percent, respectively (Panel A).

Panel B of Table 1 reports the number of sales events by account type and client segment. Each day on which an investor places a sell order is considered a sales event, and sales events from different accounts are treated as different observations.[10] Of these sales events, 63.5 percent are from margin accounts, 11.1 percent from cash accounts, and 25.4 percent from retirement accounts. When sales events are classified by client segment, active traders account for the largest fraction of total sales events (50.3 percent).

Panel C describes the characteristics of investor portfolios on the days of stock sales, aggregated over all sales events. Investors' portfolios are constructed from their purchase records since January 1991 and the profiles of investor portfolios are examined at the sales event. The median portfolio size and the number of stocks in the portfolio over all sales events are $45,406 and 5 for the entire sample. Investors on average have more winners than losers (median num-

[9]The results are not very sensitive to the way winners and losers are defined. The results are qualitatively the same when the first or the most recent purchase price is used as a reference point, when commissions are added to the purchase price and deducted from the sales price, and when stocks sold at reference prices are considered winners or dropped from the analysis.

[10]Suppose there are only two accounts in the sample, Account 1 and Account 2. Account 1 sold stock A and stock B on October 9, 1991, and stock C on November 14, 1992. Account 2 sold stock B and stock C on November 14, 1992. In this hypothetical example, the number of sales events is three (two from Account 1 and one from Account 2).

ber of winners: 3; median number of losers: 2), and the dollar value of a winner is greater than that of a loser (the medians are $8,725 and $5,577, respectively).[11]

4.2 Proportion of Multiple Stock Sales Conditional on Gains or Losses

Figure 3 shows the distribution of the time interval between two consecutive stock sales from the same account, separately for the sales of winners and for the sales of losers. There is not much difference between the sales of winners and the sales of losers for the intervals greater than 5 days, but there is a clear difference between them for the interval of 0 to 5 days. About 24 percent of sales of losers occur on the same day as another sale of losers, while 17 percent of sales of winners occur on the same day as another sale of winners. We can see from Figure 3 that the sales of losers tend to be bundled on the same day compared to the sales of winners.

Table 2 reports the number of sales events separately for those at gains and those at losses. To examine whether losses are more likely to be bundled than gains, sales events are classified by whether the sales are at gains or at losses and whether or not the investor sold multiple stocks on that day. Investors also prefer to aggregate a loss with a larger gain according to the hedonic editing hypothesis. However, I discard sales events with mixed sales in this cross-classification analysis since they are associated with both gains and losses. About 5.95 percent of the observations are deleted because they are mixed sales (25,337 out of 425,749 observations).

Panel A of Table 2 documents the results for the entire sample. When investors are selling stocks at losses, they sell multiple losers in 10.44 percent of the cases, while they sell multiple winners in 8.48 percent of the cases where they realize gains. The difference between the two proportions is 1.96 percent, which is highly significant with a t-statistic of 20.01.[12] The results show that losses are more strongly associated with bundling than are gains.

[11]Since portfolios are constructed from the purchase records since 1991, the number of stocks and the portfolio sizes reported in Table 1 are not very accurate. On the one hand, they are likely to be downward-biased since they do not include stocks that were purchased prior to 1991. On the other hand, averaging over sales events instead of examining month-end positions can inflate the numbers by disproportionately representing portfolios of the investors who trade frequently and are likely to have larger portfolios. Barber and Odean (2000) report that the mean household holds 4.3 stocks worth $47,334 and the median household holds 2.61 stocks worth $16,210, which are calculated from the month-end position statements.

[12]The standard errors are calculated under the assumption that all sales events are independent.

Panel B shows the results by client segment. Affluent households show the greatest difference between sales at losses and sales at gains in their propensities to sell multiple stocks (2.78 percent), and active trader households show the smallest difference (1.58 percent). All the differences are highly significant.

4.2.1 Tax-loss selling

It is well known that investors tend to realize losses near the end of the year to take advantage of tax deductions from capital losses. When sales events are classified by month, the difference is especially large in December. Investors sell multiple losers in 14.18 percent of the sales events at losses and sell multiple winners in 7.93 percent of the sales events at gains (difference: 6.25 percent; Panel C, Table 2) in December. The result suggests that tax-loss selling is likely to cause clustering of loss selling. However, tax-loss selling may not be the only cause since the difference between the two proportions is still significant (1.41 percent; t-statistic: 13.82) from January through November.

An alternative way of addressing the tax-loss selling hypothesis is to look at stock sales from retirement accounts (IRA/Keogh). Panel A of Table 3 documents the results separately for taxable and retirement accounts. As expected, the difference between sales events at gains and sales events at losses in the proportions of multiple stock sales is larger for the taxable accounts (2.01 percent; t-statistic: 17.58). However, the difference for the retirement accounts is also positive and highly significant (1.69 percent, t-statistic: 8.87). Tax-loss selling seems to play a role in the clustering of loss selling, but it does not explain why investors are more likely to sell losers than to sell winners on the same day from their retirement accounts.

4.2.2 Margin calls

Stock price drops may trigger margin calls and force investors to sell some of the stocks in their portfolios. It is likely that there are more losers than winners in the accounts that have just experienced margin calls; therefore, margin calls may result in sales of multiple losers more often than sales of multiple winners.

Margin trades are not allowed for certain types of accounts (cash or retirement accounts), so

Panel B of Table 3 reports results separately for accounts that allow margin trading and those that do not allow margin trading. The difference between gains and losses in the percentage of multiple stock sales is actually greater for non-margin accounts (1.81 percent for margin accounts and 2.12 percent for non-margin accounts), which indicates that margin calls are not the primary reason for clustering of loss selling. In both margin and non-margin accounts, the differences are all significant.

4.2.3 Number of winners and losers & Difference in preferences across investors

Investors might simply have more losers than winners; therefore, they may sell multiple losers more often than multiple winners as they have more losers available for sale.[13] It is also possible that a certain group of investors always prefer selling multiple stocks at a time regardless of whether the stocks are winners or losers. If those investors happen to have mostly losers rather than winners, the higher proportion of multiple stock sales in loss sales events could be due to differences in investor characteristics, not because investors prefer integrating losses and segregating gains.

To control for these possibilities, only sales events for which there are equal number of winners and losers in the corresponding portfolio are examined in Table 4. This restriction ensures that investors had equal opportunities to sell winners and losers and also controls for the possibility that differences in individual characteristics might be driving the results.

The results are qualitatively the same after imposing the restriction of equal numbers of winners and losers (Table 4). The restriction reduces the number of observations from $400,412$ to $64,253$ (about 16 percent of the original sample). The difference in the proportions of multiple stock sales is reduced as well (1.96 percent for the entire sample vs. 1.64 percent for the restricted sample), but still remains significant. The result shows that investors are more likely to sell multiple stocks when they realize losses than when they realize gains, even though they have equal opportunities to sell winners and losers. Also, it rules out the possibility that investor characteristics are solely responsible for the finding. If the asymmetry is driven by a certain group of investors, who happen to have mostly losers, always prefer selling multiple

[13]However, Table 1 shows that investors actually have more winners than losers.

stocks, we should not observe the asymmetry in this restricted sample.

Because investors' portfolios for this study are constructed from their purchase records since 1991, stocks that were purchased prior to 1991 are not counted. Thus, the number of stocks in the portfolio in this analysis is downward biased, and the bias is likely to be greater for the number of losers because investors tend to sell winners early and hold on to losers (e.g., Shefrin and Statman (1985), Odean (1998)). This indicates that there could be more losers than winners among stocks that were purchased before 1991 therefore not counted in the analysis. In that case, the restriction of equal numbers of losers and winners may actually result in a sample with more losers than winners, biasing the results toward finding more bundling of losers.

To address this possible bias of omitted stocks, Panel B reports the results separately for the sub-periods from 1991 to 1994 and from 1995 to 1996. When holding periods are calculated from the round-trip transactions, less than 1 percent of stocks are held for four years or longer. Thus, the bias from omitted stocks should be minimal in the later part of the sample period. The differences in proportions are quite similar in these two sub-periods, suggesting that the bias does not affect the result very much (1.66 percent in the period of 1991-1994, vs. 1.60 percent in the period of 1995-1996)

4.2.4 Difference in sales proceeds

Investors may sell stocks for liquidity reasons. The number of stocks an investor needs to sell to reach a desired level of proceeds depends on the dollar value of each stock in his portfolio. Since the dollar values of losers are on average smaller than the dollar values of winners (Table 1, Panel C), investors may need to sell a larger number of stocks when they sell losers than when they sell winners to reach the same level of proceeds. If so, stock sales for liquidity needs could be responsible for the observed pattern in investors' selling behavior.[14] To address this alternative argument, Table 5 examines a subset of the sample selected based on the potential proceeds from sales of winners and losers.

[14]However, this alternative argument is not very convincing if the commission structure is taken into account. Commissions are usually charged on a per trade basis, which means that investors should sell one stock rather than multiple stocks to minimize commission charges given the same proceeds.

For each sales event, the average dollar value per stock is calculated separately for winners and losers in the investor's portfolio. Panel A of Table 5 reports the result when the average dollar values of losers and winners in the same portfolio are close to each other (when the difference between the two is less than 10 percent); Panel B reports the result when the average dollar value of losers is greater than the average dollar value of winners in the same portfolio.

The difference between gains and losses in the proportion of multiple sales is 1.12 percent, with a t-statistic of 3.02 (Panel A, Table 5) when winners and losers have similar dollar values. The difference is 1.00 percent (t-statistic: 4.74) when losers have larger dollar values than winners. Although the differences are smaller than those in the previous tables, they are still statistically significant.

4.2.5 Commonality among winners and among losers

If losers in a portfolio are more related to each other than are winners, losers are more likely subject to common shocks than winners, contributing to the clustering of loss selling. For example, daily stock returns of losers could be more highly correlated than those of winners in the same portfolio, or the proportion of losers in similar industries could be greater than that of winners. I report various measures of relatedness separately for winners and for losers based on return correlations and industry membership in Table 6 to investigate if losers are more related to each other than winners.

For each sales event, the portfolio from which sales occur is divided into a winner and a loser portfolio. Indices of relatedness (RI) and the mean and maximum correlations ($CORR$,$MXCORR$) of the winner and loser portfolios are calculated by pair-wise comparisons of all possible pairs of winners and losers within each of their respective portfolios. Specifically, for sales event k, the index of relatedness and the mean and maximum correlations of the winner and loser portfolios are calculated as follows ($\bullet$ denotes either W or L):

$$RI_k^{\bullet} = \frac{\sum\limits_{i,j \in S_k^{\bullet}, i<j} I_{ij}}{\sum\limits_{i,j \in S_k^{\bullet}, i<j} 1}, \quad CORR_k^{\bullet} = \frac{\sum\limits_{i,j \in S_k^{\bullet}, i<j} \rho_{ij}}{\sum\limits_{i,j \in S_k^{\bullet}, i<j} 1}, \quad MXCORR_k^{\bullet} = \max_{i,j \in S_k^{\bullet}, i<j} \rho_{ij}, \tag{1}$$

where I_{ij} is an indicator variable equal to 1 if stock i and stock j belong to a same industry group, and ρ_{ij} is the correlation of daily stock returns of stocks i and j over 90 days prior to the sales event. S_k^W (S_k^L) is the winner (loser) portfolio for sales event k. For the definition of industry groups, two alternative definitions based on 2-digit SIC codes are used to make sure that the results are robust to different methods of industry grouping. The index of relatedness using 12 industry groups following Ferson and Harvey (1991) is denoted $RI(FH)$ and the index using 19 industry groups following Moskowitz and Grinblatt (1999) is denoted $RI(MG)$. The index of relatedness and the mean and maximum correlations of winner and loser portfolios are first calculated at the sales event level, then averaged across sales events ($N^W (N^L)$ is the total number of winner (loser) portfolios).

$$RI^{\bullet} = \frac{\sum\limits_k RI_k^{\bullet}}{N^{\bullet}}, \quad CORR^{\bullet} = \frac{\sum\limits_k CORR_k^{\bullet}}{N^{\bullet}}, \quad MXCORR^{\bullet} = \frac{\sum\limits_k MXCORR_k^{\bullet}}{N^{\bullet}}. \tag{2}$$

Table 6 reports the averages of the indices of relatedness and the averages of mean and maximum correlations of daily stock returns for winner and loser portfolios. The index of relatedness is higher and the mean and maximum correlations of returns are greater for winner portfolios than for loser portfolios, indicating that winners are more related to each other than are losers.

It is possible that the indices of relatedness and the mean and maximum correlations of the portfolio are sensitive to the number of stocks in the portfolio. To check whether the results are sensitive to the number of stocks in the portfolio, the results are reported by the number of stocks in each winner/loser portfolio as well. The results are robust in relation to the number of stocks in the portfolio.

Table 6 shows that winners are more related to each other than losers in their industry membership and correlations of stock returns. If some kind of commonality among stocks drives clustering of sales, it should increase the probability of multiple sales of winners rather than multiple sales of losers. Thus, it does not appear that commonality among stocks is responsible for the main finding.

4.2.6 Delays in order execution

It may take longer than a day for good-till-cancel limit orders to be executed, therefore some of sales events that are counted separately might be from limit orders that were placed on the same day but executed over a few days. Linnainmaa (2003) finds that investors are more likely to submit limit orders when they realize gains than losses.[15] If investors are more likely to use limit orders when they realize gains than losses, investors may appear to realize their gains over different days relative their losses even though they are equally likely to bundle sales of winners and sales of losers.

There is no information on whether a trade is from a limit order or from a market order in the data set, so I perform three different tests to control for the effect of stale limit orders. First, I look at sales events in which sales price is lower than the closing price of the previous trading day and sales quantity is smaller than the previous day's trading volume (Panel A of Table 7). If a stock is sold at a price that is lower than the closing price of the previous trading day and if there was enough trading volume on the previous day, it is probably safe to assume that the order was placed on the same day. If the order had been placed on the previous day or earlier, it would have been executed on the previous day which closed with a higher price than the limit price. Secondly, I examine sales events in which none of sales are at round or half dollars (Panel B). Goetzmann and Zhu (2003) argue that limit orders are more likely to take place at round dollars or half dollars since investors are more likely to use rounding when setting limit order prices. If so, sales events that are examined in Panel B are likely to consist of market orders. Lastly, sales events that are far apart from other sales events from the same account are examined in Panel C. The reason why delays in order execution may bias the results for finding more bundling of losses than gains is that one sales event with

[15] There are no market orders in Finland. Linnainmaa (2003) classifies orders that are not immediately executed as limit orders and as market orders otherwise.

multiple winner sales based on the timing of order *submission* can be counted as two or more sales events with a single winner sale based on the timing of order *execution.* As long as orders placed on the same day are counted as one sales event, delays in execution do not bias the results. Panel C identifies sales events that are not likely to be associated with this kind of sales events double-counting. Delay in order execution is likely to be relatively short, probably less than a few days. If delays in order execution resulted in two or more sales events when there is actually only one sales event based on order submission timing, those sales events are likely to be within a few days of each other. If there is no other sales event in the 15-day window around the sales event ([-7,7]),[16] it suggests there is no other sales event resulting from orders placed on the same day and executed on a different day. Thus, sales events examined in Panel C are not likely to be associated with double-counting of sales events due to stale limit orders.

All results in Table 7 show that investors' propensity to sell multiple stocks is greater when they realize losses than gains after excluding sales events that are possibly contaminated by stale limit orders. Therefore, delays in limit order execution does not appear to be driving the result.

4.2.7 Account level analysis

So far, the propensity to sell multiple stocks is calculated by aggregating across sales events from all accounts. As an alternative, the propensity to sell multiple stocks is calculated at the account level in Table 8. The propensity to sell multiple stocks when the account realizes losses and when it realizes gains and the difference between the two are calculated for each account and then aggregated across accounts.

Let N^i_{ml} (N^i_{sl}) be the number of sales events when account i sells multiple losers (one loser). Similarly, N^i_{mg} (N^i_{sg}) is the number of sales events when account i sells multiple winners (one winner). The difference in the proportion of sales events with multiple stock sales conditional on gains and losses is calculated for each account for which there are at least five sales events, and the differences are aggregated across accounts, as follows:

[16]The results are almost the same when I use longer windows like [-14,14].

$$DIFF^i = \frac{N^i_{ml}}{N^i_{ml} + N^i_{sl}} - \frac{N^i_{mg}}{N^i_{mg} + N^i_{sg}} \ , \quad DIFF = \frac{\sum_i DIFFi}{\#\ of\ accounts}. \tag{3}$$

The account level analysis yields results very similar to the aggregated result. On average, the propensity to sell multiple stocks is larger when investors realize losses rather than when they realize gains, and the average difference between the two propensities is 1.96 percent.

4.3 Logistic Analysis of the Determinants of Multiple Stock Sales

A logistic regression approach allows simultaneous examination of many determinants of multiple stock sales, while the cross-classification method used in the previous section allows examination of only one or two determinants at a time. The following logistic model is used to examine whether or not realizing losses increases the propensity of investors to sell multiple stocks:

$$Pr(Multi = 1) = \Lambda(\beta_0 + \beta_1 LOSS + \sum_{k=2}^{n} \beta_k x_k + \varepsilon), \tag{4}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function. For each sales event, the dependent variable is a binary variable that takes the value of one if multiple stocks are sold on the sales event and zero if only one stock is sold. $LOSS$ is an indicator variable that takes the value of one if the sales are at losses and 0 if they are at gains. The x_ks are control variables. As in the previous section, sales events in which investors sell both a winner and a loser are dropped from the analysis.

For the controls, a dummy variable for sales events from margin accounts (MARGIN) and a dummy variable for sales events from taxable accounts (TAX) are included because margin trading and tax-loss selling can contribute to the multiple stock sales. Also included are a dummy for sales in December (DEC), a natural log of the number of stocks in the portfolio (Log(NSTOCK)), the value-weighted average of the holding period returns of stocks in the portfolio (VWHPRET), the average of the squared daily market returns calculated over days $[-60, -1]$ (MKTVOL), four market return variables (MKTRET) and four portfolio return variables (PFRET) that cover the sales date and 20 trading days prior to the sales event date (days 0, -1, $[-5,-2]$, $[-20,-6]$).[17] Other control variables are the average dollar amount position of a stock in the portfolio (DPOSI), a dummy variable equal to 1 if the account makes purchases on the same day (PURCHASE), and two dummy variables that represent the client segment, one for the active traders (TRADER) and the other for the affluent households (AFFLUENT). The total number of stock sales from all accounts in the data set on the same day (NTSALES) is included as a proxy for the overall selling activity on that day. Also included are interaction terms of LOSS with a taxable account dummy and a December sales dummy (LOSS*TAX, LOSS*DEC, LOSS*TAX*DEC).

Table 9 reports maximum likelihood estimates of regression coefficients and their robust standard errors. The results in Table 9 confirm the univariate results. Investors are more likely to sell multiple stocks when they realize losses, after controlling for the effect of the number of stocks in the portfolio, account and household characteristics, the average dollar value of the stocks in the portfolio, overall selling activity during the day, market volatility, and the current and past portfolio and market returns. The coefficient for the variable LOSS is positive and significant at the one percent level across all models. Since interaction terms of the LOSS variable with the DEC and TAX dummies are included as well, the coefficient of LOSS represents the effect of realizing losses on the probability of multiple stock sales in non-December months for non-taxable accounts. The coefficient estimate of LOSS*TAX*DEC is positive and highly significant, but LOSS*TAX and LOSS*DEC are not significant. This shows that tax-loss selling in December increases the probability of multiple stock sales, confirming the results in the univariate tests.

The value-weighted holding period return of the portfolio, VWHPRET, is negatively related to the probability of multiple stock sales. VWHPRET is closely related to whether the investor realizes losses or gains at the sales event, therefore likely to take away significance from the LOSS dummy. However, the LOSS variable remains significantly positive after controlling for the holding period returns and portfolio returns prior to and on the sales events. Adverse market movements prior to the sales and especially on the sales date increase the probability of

[17] Grinblatt and Keloharju (2000) find that returns beyond a month (about 20 trading days) in the past appear to have little impact on the decision to sell a stock.

multiple stock sales. It also appears that investors sell multiple stocks in highly volatile markets and on days when there is a high level of selling activity, as the coefficients for MKTVOL and NTSALES are positive and significant. Also, the coefficient of the PURCHASE dummy is positive and highly significant. It is possible that sales with accompanying purchases occur when investors rebalance their portfolios, and portfolio rebalancing is likely to result in multiple stock sales. In the last column, I replace Log(NSTOCK) with a set of dummies, one for each number of stocks up to NSTOCK=25, and one for NSTOCK>25.[18] Using a set of dummies for the number of stocks increases the model fit, but does not change the results very much.

4.4 Modeling Stock Sales as Independent Bernoulli Trials

As an alternative approach, the probability of observing multiple stock sales is modeled assuming the decision to sell one stock is independent of the decision to sell other stocks. This provides a benchmark for what we should expect about the probability of multiple stock sales if there is no dependency; that is, if there is no intentional bundling or separating of sales.

Suppose that whether a stock is sold is modeled as an independent Bernoulli trial.[19] Then the probability of multiple stock sales from an investor on a given day is a function of the number of winner and loser stocks in the portfolio and the propensity of the investor to sell each winner and loser. If the investor has n_g winners and n_l losers in his/her portfolio and the probability that he/she sells each winner (loser) is p_g (p_l), then the probability of multiple stock sales during a sales event is

$$Pr(Multi = 1) = Pr(n_s \geq 2 | n_s \geq 1)$$

$$= \frac{1 - (1-p_g)^{n_g}(1-p_l)^{n_l} - n_g p_g (1-p_g)^{n_g-1}(1-p_l)^{n_l} - n_l p_l (1-p_g)^{n_g}(1-p_l)^{n_l-1}}{1 - (1-p_g)^{n_g}(1-p_l)^{n_l}}, \quad (5)$$

where n_s is the number of stocks that the investor sells.

Figure 4 shows the logit of the probability of multiple sales as a function of n_g and n_l when $p_g = 0.148$ and $p_l = 0.098$.[20] It shows that the logit of the probability of multiple stock

[18]NSTOCK is greater than 25 for less than 5% of the sample.

[19]Odean's (1998) PGR (proportion of gains realized) and PLR (proportion of losses realized) methodology is based on the same assumption.

[20]The values of p_g and p_l are based on Odean's (1998) results.

sales increases with the number or winners (n_g) and the number of losers (n_l) almost linearly except for the lowest values of n_g and n_l. Intuitively, multiple stock sales are more likely if the investor's propensity to sell each stock is greater. Alternative views of the figure are also presented by fixing n_l (n_g) at 5. The probability of multiple stock sales increases more rapidly with the number of winners than with the number of losers, since investors are more likely to sell a winner than to sell a loser ($p_g > p_l$).

Suppose we estimate the following logit model:

$$Pr(Multi = 1) = \Lambda(\alpha + \beta_g n_g + \beta_l n_l + \varepsilon) \tag{6}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function, equivalent to modeling the logit of $Pr(Multi = 1)$ as a linear function of n_g and n_l. The estimated coefficients for the number of winners and the number of losers (β_g and β_l) are related to investors' propensities to sell a winner and a loser, respectively. If we believe that investors are more likely to sell a winner than to sell a loser as the disposition effect implies ($p_g > p_l$: e.g., Odean (1998)) and that the decision to sell each stock is independent, we expect $\beta_g > \beta_l$. But if we observe $\beta_g < \beta_l$, this indicates that sales decisions of losers are positively correlated, or at least that sales decisions of losers are more positively (less negatively) correlated than sales decisions of winners, reversing the relationship between these two coefficients.

Table 10 presents the coefficient estimates the following model:

$$Pr(Multi = 1) = \Lambda(\alpha + \beta_g n_g + \beta_l n_l + \sum_{k=1}^{n} \beta_k x_k + \varepsilon), \tag{7}$$

where the x_k's are control variables similar to those used in Table 9. This specification allows for sales of winners and losers at the same time; mixed sales in which winners and losers are sold together are therefore included in this analysis.

Table 10 shows that the estimate of β_l is always greater than the estimate of β_g across different specifications. Chi-square test statistics for the equality of these two coefficients reject the null hypothesis, $H_0 : \beta_g = \beta_l$, at the one percent level.

If there is no dependency in the sales decisions of different stocks, β_l will be greater than β_g only if $p_l > p_g$. However, a vast amount of empirical evidence on the disposition effect (see footnote 1) shows that a loser is less likely to be sold than a winner ($p_l < p_g$). The results in Table 9 provide further evidence that selling decisions on losers are more positively correlated with each other than are the selling decisions on winners.

5 Discussion

This study derives a testable implication from Thaler's (1985) mental accounting principles on investors' trading behavior, and presents evidence consistent with the prediction. In this section, I discuss how the mental accounting principles are related to broader issues about the behavior of various market participants.

Shefrin and Statman (1993) suggest that the design of financial products may be guided by the mental accounting principles. They describe how brokers promote covered calls by framing the cash flow of a covered call into three mental accounts or "three sources of profit" – the call premium, the dividend, and the capital gain on the stock. By segregating gains, brokers can make covered calls more attractive to their clients.

Loughran and Ritter (2002) offer a possible explanation for why issuers seem willing to leave large amounts of money on the table during IPOs. They argue that the loss from underpricing will be aggregated with a larger gain from the retained shares. Issuers will therefore not be upset by the large initial underpricing.

If investors are more likely to integrate concurrent events, firms may have an incentive to time their disclosures strategically to take advantage of investor preferences. Companies sometimes manage their income statements by accounting choices to make poor results look even worse ("take a big bath"). It has been argued that this method is often utilized in a bad year to artificially enhance next year's earnings.[21] Several explanations have been offered for firms' incentives to smooth earnings. However, it is somewhat puzzling why firms smooth earnings and also occasionally take big baths. Mental accounting of multiple outcomes provides

[21]For example, Gateway threw all the company's bad news into the third quarter in 1997, reporting a net loss of 68 cents a share. After taking an initial 22 percent hit, however, Gateway shares were up 83 percent by September 1998. This maneuver may have helped the company subsequently report its best gross margins in years – 19.5 percent and 20.6 percent in the first two quarters of 1998. ("Gateway's Big Bath," by Eric Moskowitz, 9/21/98, http://www.thestreet.com/stocks/accounting/19863.html).

an alternative explanation for the coexistence of these seemingly opposite behaviors.[22] The principle of segregation of multiple gains suggests that stock prices will be, on average, higher if the manager spreads out good news over time by income smoothing. In contrast, for sufficiently bad news, it is better to report a big loss and possibly improved profits in later periods rather than reporting two separate small losses. Investors will be less upset when losses are integrated or a small gain is segregated from a large loss, as suggested by the principle of integration of multiple losses or the principle of segregation of a small gain from a larger loss. Therefore, managers who try to maximize stock prices have incentives to take big baths and smooth earnings.[23]

6 Conclusion

This paper examines whether mental accounting of multiple outcomes influences the way investors sell stocks. I find that investors are more likely to sell multiple stocks when they realize losses than gains. The result can be interpreted as evidence supporting the hedonic editing hypothesis (Thaler (1985)), according to which individuals try to integrate losses and segregate gains. Alternative explanations that are based on tax-loss selling strategies, margin calls, the number of losers and winners in the portfolio, the difference in the potential proceeds from selling winners and losers, correlations among winners and among losers, and possible delays in order execution do not fully account for the observed behavior.

This study has relevance for several strands of research. Recent studies have provided possible explanations for many empirical puzzles in the stock market by incorporating joint implications of prospect theory and mental accounting into the models. These studies and possible future developments along that line can benefit from the direct test of the underlying psychological theories on the actual behavior of market participants provided in this paper. In addition, the empirical results complement other recent studies on the trading behavior

[22] A few recent studies (e.g., Koch and Wall (2000) and Kirschenheiter and Melumad (2002)) have addressed this question under a rational framework.

[23] The mental accounting principles in Thaler (1985) are concerned with evaluation of sure outcomes. Mental accounting also plays an important role in the evaluation of uncertain outcomes. Studies have shown that the way lotteries are evaluated influences how attractive the overall lottery is (e.g., Gneezy and Potters (1997), Thaler, Tversky, Kahneman, and Schwartz (1997), Langer and Weber (2001)).

of individual investors by showing how selling decisions on multiple stocks interact with each other. Furthermore, this paper may have implications on equilibrium asset prices in light of Barberis and Huang (2001). Barberis and Huang (2001) have shown that different forms of mental accounting generate different predictions about stock returns. If the way investors mentally account for their investments depends on whether they have gains or losses, then this study suggests a possible way to identify which mental accounting system is used by investors, which can help us better understand stock market behavior.

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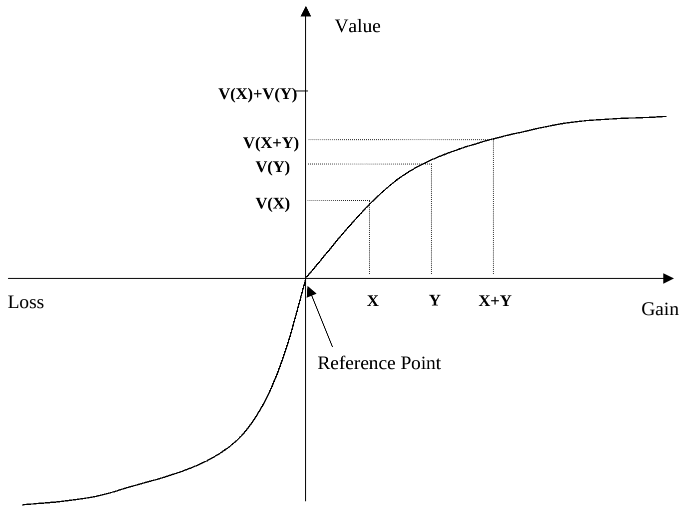

Figure 1: Multiple Gains - Segregation Preferred

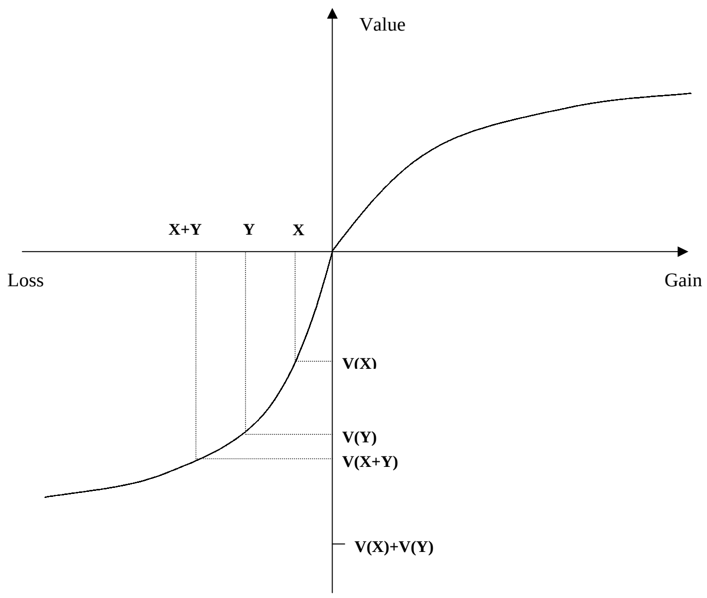

Figure 2: Multiple Losses - Integration Preferred

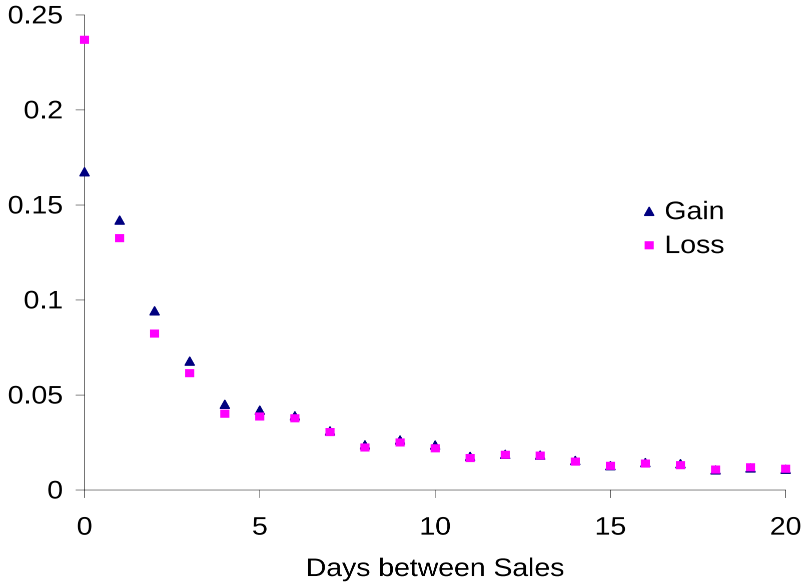

Figure 3: Distribution of the Interval between Sales

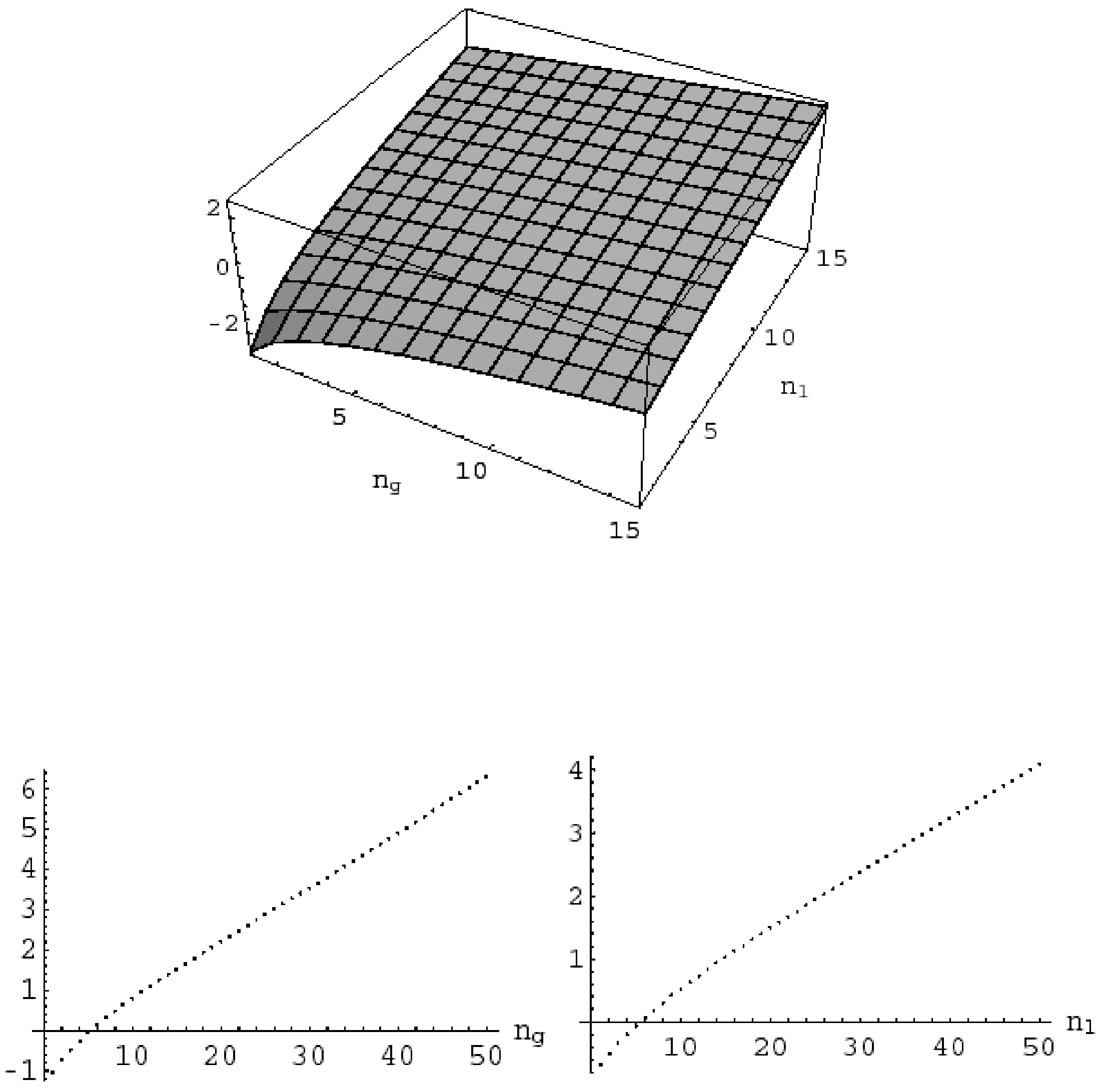

Figure 4: Logit of the Probability of Multiple Stock Sales as a Function of the Number of Winners (n_g) and Losers (n_l) ($p_g = 0.148$, $p_l = 0.098$)

Table 1. Sample Descriptive Statistics

Table 1 summarizes the sample of individual investor trades used in the study. The data contains records of each investor's trades in common stocks during the period from January 1991 to November 1996. All same-day trades in the same stock by the same account are aggregated, and all sales without matching purchase records are discarded. Each day when an account sells a stock is considered one sales event. Sales events in which the entire positions are liquidated are dropped from the sample.

Panel A. Number of Accounts

By Account Type			By Client Segment		
Cash	8,623	17.2%	Affluent	9,169	18.3%
Margin	24,629	49.0%	General	29,853	59.4%
IRA/Keogh	16,977	33.8%	Trader	11,207	22.3%
All	50,229				

Panel B. Number of Sales Events

By Account Type			By Client Segment		
Cash	47,178	11.1%	Affluent	45,770	10.8%
Margin	270,386	63.5%	General	165,757	38.9%
IRA/Keogh	108,180	25.4%	Trader	214,217	50.3%
All	425,744				

Panel C. Portfolio Characteristics at Sales Events

	Portfolio Size	Dollar Value per Stock	Dollar Value per Stock - Winner	Dollar Value per Stock - Loser	# of Stocks	# of Winners	# of Losers
Mean	$156,089	$17,922	$20,964	$13,501	8.6	4.6	3.9
Median	$45,406	$7,792	$8,725	$5,577	5	3	2

Table 2. Proportion of Multiple Stock Sales - Gain vs. Loss

Table 2 cross-classifies sales events by whether the sales are at gains or at losses and the number of stocks sold during the day. Each (account, sales date) pair is regarded as one observation. If an investor sells both a loser and a winner on the same day, the observation is dropped. All same-day trades in the same stock by the same account are aggregated and all sales without matching purchase records are discarded. The number of observations that belong to each 2x2 cell is reported. The proportion of sales events with multiple stocks is calculated separately for losses and gains and the difference between the two are reported with t-statistics. T-statistics are calculated based on the assumption that all sales events are independent.

Panel A. Entire Sample

	# of stocks sold		Multiple stock	# Obs
	1	≥ 2	sales %	
Loss	126,296	14,722	10.44%	400,412
Gain	237,406	21,988	8.48%	
Difference			1.96%	
t-stat			20.01	

Panel B. By Client Segment

	Affluent			General			Trader		
	# of stocks sold		Multiple stock	# of stocks sold		Multiple stock	# of stocks sold		Multiple stock
	1	≥ 2	sales %	1	≥ 2	sales %	1	≥ 2	sales %
Loss	13,560	1,490	9.90%	50,651	4,770	8.61%	62,085	8,462	11.99%
Gain	26,501	2,031	7.12%	96,039	6,596	6.43%	114,866	13,361	10.42%
Difference			2.78%			2.18%			1.58%
t-stat			9.69			15.40			10.56

Panel C. Jan.-Nov. vs. December

	Jan.-Nov.			December		
	# of stocks sold		Multiple stock	# of stocks sold		Multiple stock
	1	≥ 2	sales %	1	≥ 2	sales %
Loss	111,593	12,292	9.92%	14,703	2,430	14.18%
Gain	222,899	20,738	8.51%	14,507	1,250	7.93%
Difference			1.41%			6.25%
t-stat			13.82			18.24

Table 3. Proportion of Multiple Stock Sales - By Account Characteristics

Table 3 cross-classifies sales events by whether the sales are at gains or at losses and the number of stocks sold during the day. Each (account, sales date) pair is regarded as one observation. All same-day trades in the same stock by the same account are aggregated and all sales without matching purchase records are discarded. The number of observations that belong to each 2x2 cell is reported. The proportion of sales events with multiple stocks is calculated separately for losses and gains and the difference between the two are reported with t-statistics. T-statistics are calculated based on the assumption that all sales events are independent.

Panel A. Taxable vs. Retirement Accounts

	Taxable Accounts			**Retirement Accounts**		
	# of stocks sold		Multiple stock	# of stocks sold		Multiple stock
	1	≥ 2	sales %	1	≥ 2	sales %
Loss	96,255	11,579	10.74%	30,041	3,143	9.47%
Gain	173,733	16,614	8.73%	63,673	5,374	7.78%
Difference			2.01%			1.69%
t-stat			17.58			8.87

Panel B. Margin vs. Non-Margin Accounts

	Margin Accounts			**Non-Margin Accounts**		
	# of stocks sold		Multiple stock	# of stocks sold		Multiple stock
	1	≥ 2	sales %	1	≥ 2	sales %
Loss	81,989	9,978	10.85%	44,307	4,744	9.67%
Gain	146,994	14,600	9.03%	90,412	7,388	7.55%
Difference			1.81%			2.12%
t-stat			14.53			13.40

Table 4. Proportion of Multiple Stock Sales: Equal Numbers of Winners and Losers

Table 4 cross-classifies sales events by whether the sales are at gains or at losses and the number of stocks sold during the day, conditional on the number of winners and losers in the portfolio being equal. Each (account, sales date) pair is regarded as one observation. All same-day trades in the same stock by the same account are aggregated and all sales without matching purchase records are discarded. The number of observations that belong to each 2x2 cell is reported. The proportion of sales events with multiple stocks is calculated separately for losses and gains and the difference between the two are reported with t-statistics. T-statistics are calculated based on the assumption that all sales events are independent.

Panel A. Entire Sample

	# of stocks sold		Multiple stock	
	1	≥ 2	sales %	# Obs
Loss	20,165	1,210	5.66%	64,253
Gain	41,155	1,723	4.02%	
Difference			1.64%	
t-stat			8.91	

Panel B. 1991-1994 vs. 1995-1996

	1991-1994			1995-1996		
	# of stocks sold		Multiple stock	# of stocks sold		Multiple stock
	1	≥ 2	sales %	1	≥ 2	sales %
Loss	12,649	736	5.50%	7,516	474	5.93%
Gain	26,382	1,054	3.84%	14,773	669	4.33%
Difference			1.66%			1.60%
t-stat			7.25			5.15

Table 5. Proportion of Multiple Stock Sales - Potential Proceeds Control

Table 5 cross-classifies sales events by whether the sales are at gains or at losses and the number of stocks sold during the day, when the difference in the average dollar values of winners and losers is less than 10% as of the sales date (Panel A), and when the average dollar value of losers is greater than the average dollar value of winners in the same portfolio. Each (account, sales date) pair is regarded as one observation. All same-day trades in the same stock by the same account are aggregated and all sales without matching purchase records are discarded. The number of observations that belong to each 2x2 cell is reported. The proportion of sales events with multiple stocks is calculated separately for losses and gains and the difference between the two are reported with t-statistics. T-statistics are calculated based on the assumption that all sales events are independent.

Panel A. Difference in dollar values less than 10%

	# of stocks sold		Multiple stock	
	1	≥ 2	sales %	# Obs
Loss	9,267	1,155	11.08%	30,879
Gain	18,420	2,037	9.96%	
Difference			1.12%	
t-stat			3.02	

Panel B. The dollar value of losers greater than the dollar value of winners

	# of stocks sold		Multiple stock	
	1	≥ 2	sales %	# Obs
Loss	27,246	2,822	9.39%	77,796
Gain	43,725	4,003	8.39%	
Difference			1.00%	
t-stat			4.74	

Table 6. Correlations of Returns and Index of Relatedness

Table 6 shows various measures of relatedness of winners and losers in a portfolio. On each sales event, the investor's portfolio is divided into a winner and a loser portfolio and correlations of daily stock returns calculated over days [-90,-1] are computed for all possible pairs of winners and losers within each of their respective portfolios. The mean and maximum of the correlations of each winner/loser pair are calculated at the sale event level and aggregated across sales events. CORR is the average of the mean correlations and MXCORR is the average of the maximum correlations of returns computed across sales events. Similarly, percentages of winner pairs and loser pairs that belong to same industries (RI) within each of their respective portfolios are computed at the sales event level and aggregated across all sales events. Two alternative definitions of industry groups are used. RI (FH) uses 12 industry groups as in Ferson and Harvey (1991), and RI (MG) uses 19 industry groups as in Moskowitz and Grinblatt (1999). n is the number of stocks in the winner/loser portfolio. T-statistics are calculated assuming unequal variances.

		# obs	RI (FH)	RI (MG)	CORR	MXCORR
All	Loser	289,373	0.1620	0.1076	0.0902	0.2653
	Winner	313,925	0.1693	0.1147	0.1274	0.3120
	Difference		-0.0073	-0.0071	-0.0372	-0.0468
	t-statistics		-11.65	-12.85	-116.49	-86.45
$n = 2$	Loser	78,356	0.1643	0.1132	0.0923	0.0932
	Winner	84,433	0.1735	0.1204	0.1271	0.1282
	Difference		-0.0092	-0.0072	-0.0348	-0.0350
	t-statistics		-4.51	-4.96	-39.85	-39.88
$n = 3$	Loser	54,302	0.1665	0.1127	0.0900	0.2079
	Winner	57,291	0.1729	0.1177	0.1271	0.2468
	Difference		-0.0064	-0.0050	-0.0371	-0.0388
	t-statistics		-3.86	-4.41	-48.76	-40.89
$n = 4$	Loser	38,096	0.1650	0.1110	0.0903	0.2727
	Winner	38,911	0.1700	0.1150	0.1272	0.3137
	Difference		-0.0049	-0.0040	-0.0369	-0.0410
	t-statistics		-3.2	-3.64	-47.67	-37.28
$5 \leq n \leq 6$	Loser	47,437	0.1606	0.1044	0.0901	0.3310
	Winner	48,909	0.1666	0.1129	0.1266	0.3724
	Difference		-0.0059	-0.0085	-0.0366	-0.0414
	t-statistics		-9.21	-6.11	-60.55	-42.94
$7 \leq n \leq 10$	Loser	40,622	0.1581	0.1006	0.0888	0.3968
	Winner	43,649	0.1640	0.1086	0.1269	0.4449
	Difference		-0.0060	-0.0079	-0.0381	-0.0481
	t-statistics		-10.12	-7.31	-68.54	-47.49
$n > 10$	Loser	30,560	0.1515	0.0939	0.0876	0.5011
	Winner	40,732	0.1639	0.1072	0.1299	0.5528
	Difference		-0.0124	-0.0133	-0.0423	-0.0517
	t-statistics		-20.73	-19.02	-81.09	-46.44

Table 7. Proportion of Multiple Stock Sales: Control for Stale Limit Orders

Table 7 cross-classifies sales events by whether the sales are at gains or at losses and the number of stocks sold during the day, after excluding sales events that are potentially contaminated by stale limit orders. Panel A examines sales events in which all sales prices are lower than the closing prices of the previous trading day and sales quantities are smaller than the previous day trading volume. Panel B examines sales events in which none of the stocks are sold at round or half dollars. Panel C examines isolated sales events, for which there are no other sales from the same account during the week before and the week after the event.

Panel A. Sales price lower than the previous day closing price

	# of stocks sold		Multiple stock	# Obs
	1	≥ 2	sales %	
Loss	67,656	5,251	7.20%	166,792
Gain	88,487	5,398	5.75%	
Difference			1.45%	
t-stat			11.89	

Panel B. No sales at round or half dollars.

	# of stocks sold		Multiple stock	# Obs
	1	≥ 2	sales %	
Loss	82,341	6,654	7.48%	240,521
Gain	142,454	9,072	5.99%	
Difference			1.49%	
t-stat			13.90	

Panel C. No other sales in the 15-day window [-7,7]

	# of stocks sold		Multiple stock	# Obs
	1	≥ 2	sales %	
Loss	82,204	8,952	9.82%	261,129
Gain	157,961	12,012	7.07%	
Difference			2.75%	
t-stat			23.63	

Table 8. Difference in the Proportion of Multiple Stock Sales: An Account Level Analysis

The difference in the proportion of multiple stock sales in sales events at losses and sales events at gains is calculated for each account with at least five sales events and then averaged across accounts. In Panel B, sales events in December are excluded.

Panel A. Entire Sample

		# Obs	DIFF	t-stat
All		16,472	1.96%	12.87
By Account Characteristics	Cash	2,016	2.79%	6.26
	IRA/Keogh	4,306	0.77%	2.59
	Margin	10,150	2.29%	11.93
By Household Characteristics	Affluent	2,180	2.67%	5.52
	General	7,789	1.98%	8.91
	Trader	6,503	1.68%	7.48

Panel B. Excluding December Sales

		# Obs	DIFF	t-stat
All		15,049	1.03%	6.59
By Account Characteristics	Cash	1,770	1.71%	3.65
	IRA/Keogh	4,047	0.89%	2.80
	Margin	9,232	0.95%	4.97
By Household Characteristics	Affluent	1,847	1.24%	2.46
	General	6,972	1.22%	5.31
	Trader	6,230	0.74%	3.23

Table 9. Logistic Analysis of the Propensity to Sell Multiple Stocks

Table 9 reports maximum likelihood estimates of regression coefficients and their z-statistics from logistic regressions. For each sales event, the dependent variable takes the value of one if multiple stocks are sold on the sales event, and zero if only a single stock is sold. Robust z-statistics adjusted for clustering on calendar dates are in parentheses.
* significant at 5% level; ** significant at 1% level

Independent variables:

LOSS	: indicator variable equal to 1 if the sales are at losses and 0 if at gains
DEC	: dummy equal to 1 for December sales
MARGIN	: dummy for margin accounts
NSTOCK	: number of stocks in the portfolio
NLOSER	: number of losers in the portfolio
NWINNER	: number of winners in the portfolio
TAX	: dummy for taxable accounts
TRADER	: dummy for active traders
AFFLUENT	: dummy variable for affluent households
DPOSI	: average dollar value of a stock in the portfolio (in million dollars)
PURCHASE	: dummy equal to 1 when the account makes purchases on the same day
NTSALES	: total number of stock sales from all accounts on day 0
VWHPRET	: value-weighted average holding period return of stocks in the portfolio
PFRET0	: value-weighted return of stocks in the portfolio on day 0
PFRET1	: value-weighted return of stocks in the portfolio on day -1
PFRET2_5	: value-weighted return of stocks in the portfolio over days [-5,-2]
PFRET6_20	: value-weighted return of stocks in the portfolio over days [-20,-6]
MKTRET0	: market return (CRSP value-weighted index) on day 0
MKTRET1	: market return on day -1
MKTRET2_5	: market return over days [-5,-2]
MKTRET6_20	: market return over days [-20,-6]
MKTVOL	: average $(\text{return})^2$ of market over days [-60,-1]

Table 9. (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOSS	0.230	0.222	0.175	0.147	0.150	0.153	0.142	0.139
	(13.44)**	(13.20)**	(6.57)**	(5.59)**	(5.71)**	(5.85)**	(5.43)**	(5.28)**
DEC		0.228	-0.138	-0.141	-0.112	-0.121	-0.114	-0.108
		(6.34)**	(-3.69)**	(-3.74)**	(-2.88)**	(-3.18)**	(-2.94)**	(-2.80)**
Log(NSTOCK)		0.692	0.673	0.682	0.686	0.686	0.685	
		(105.36)**	(89.21)**	(90.12)**	(89.87)**	(89.65)**	(89.42)**	
MARGIN		0.063	0.074	0.072	0.069	0.069	0.069	0.066
		(3.02)**	(3.54)**	(3.42)**	(3.30)**	(3.29)**	(3.28)**	(3.15)**
TAX		-0.097	-0.107	-0.107	-0.111	-0.110	-0.110	-0.100
		(-4.20)**	(-4.31)**	(-4.33)**	(-4.47)**	(-4.43)**	(-4.45)**	(-4.01)**
LOSS*DEC			0.015	0.014	0.012	0.016	0.012	0.006
			(0.17)	(0.16)	(0.14)	(0.18)	(0.14)	(0.06)
LOSS*TAX			-0.010	-0.005	-0.004	-0.004	-0.005	-0.001
			(-0.35)	(-0.18)	(-0.14)	(-0.13)	(-0.17)	(-0.04)
LOSS*TAX*DEC			0.514	0.520	0.518	0.515	0.523	0.518
			(6.38)**	(6.47)**	(6.46)**	(6.41)**	(6.52)**	(6.39)**
ACTIVE			-0.002	-0.008	-0.004	-0.004	-0.005	0.004
			(-0.16)	(-0.52)	(-0.31)	(-0.31)	(-0.32)	(0.26)
AFFLUENT			-0.065	-0.056	-0.050	-0.050	-0.050	-0.082
			(-3.15)**	(-2.68)**	(-2.39)*	(-2.40)*	(-2.41)*	(-3.96)**
DPOSI			-0.649	-0.467	-0.475	-0.480	-0.477	-0.148
			(-3.79)**	(-2.86)**	(-2.92)**	(-2.94)**	(-2.93)**	(-0.89)
NTSALES			0.001	0.001	0.001	0.001	0.001	0.001
			(14.67)**	(15.68)**	(19.16)**	(18.50)**	(19.07)**	(18.89)**
PURCHASE			0.303	0.301	0.301	0.300	0.299	0.319
			(20.60)**	(20.59)**	(20.61)**	(20.59)**	(20.57)**	(22.28)**
VWHPRET				-0.140	-0.142	-0.145	-0.138	-0.116
				(-7.70)**	(-8.07)**	(-7.92)**	(-7.65)**	(-6.74)**
MKTVOL					50.215	47.333	51.202	56.360
					(6.68)**	(6.22)**	(6.81)**	(7.49)**
MKTRET0					-6.167		-2.241	-1.845
					(-5.45)**		(-1.97)*	(-1.60)
MKTRET1					-5.642	-6.769	-5.725	-5.717
					(-4.70)**	(-5.57)**	(-4.76)**	(-4.76)**
MKTRET2_5					-1.783	-1.718	-1.526	-1.466
					(-2.98)**	(-2.76)**	(-2.44)*	(-2.36)*
MKTRET6_20					-0.207	-0.318	-0.295	-0.277
					(-0.63)	(-0.93)	(-0.87)	(-0.81)
PFRET0				-3.065			-2.778	-2.993
				(-10.24)**			(-9.73)**	(-8.97)**
PFRET1				0.043		0.043	0.050	0.055
				(2.91)**		(2.42)*	(2.67)**	(2.55)*
PFRET2_5				-0.218		-0.068	-0.125	-0.066
				(-1.10)		(-0.46)	(-0.76)	(-0.42)
PFRET6_20				0.091		0.100	0.078	0.102
				(1.24)		(1.40)	(1.11)	(1.32)
NSTOCK DUMMIES	NO	NO	NO	NO	NO	NO	NO	YES
Pseudo-R^2	0.20%	5.14%	5.76%	5.87%	5.89%	5.86%	5.93%	7.63%
Observations	400,412	400,412	400,412	400,263	400,412	400,263	400,263	400,263

Table 10. Logistic Analysis of the Propensity to Sell Multiple Stocks: An Alternative Approach

For each sales event, the dependent variable takes the value of one if multiple stocks are sold on the sales event, and zero if only a single stock is sold. See Table 9 for the definitions of independent variables. Chi-square test statistics for testing equality of the coefficient for NWINNER and the coefficient for NLOSER are reported with p-values. Robust z-statistics adjusted for clustering on calendar dates are in parentheses. * significant at 5% level; ** significant at 1% level.

Table 10. (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
NLOSER	0.043	0.043	0.039	0.036	0.036	0.036	0.035
	(31.33)**	(30.85)**	(28.24)**	(27.32)**	(28.02)**	(28.19)**	(27.66)**
NWINNER	0.029	0.029	0.023	0.025	0.026	0.025	0.026
	(21.66)**	(21.81)**	(17.44)**	(18.33)**	(19.27)**	(19.06)**	(19.52)**
DEC		0.162	0.087	0.085	0.111	0.097	0.106
		(5.86)**	(3.53)**	(3.64)**	(5.42)**	(4.51)**	(5.18)**
MARGIN		0.094	0.064	0.064	0.064	0.064	0.063
		(5.79)**	(3.95)**	(3.91)**	(3.92)**	(3.91)**	(3.88)**
TAX		-0.057	0.003	0.002	0.001	0.001	0.001
		(-3.24)**	(-0.14)	(-0.13)	(-0.03)	(-0.06)	(-0.02)
ACTIVE			0.237	0.234	0.237	0.236	0.236
			(19.67)**	(19.54)**	(20.02)**	(19.81)**	(19.89)**
AFFLUENT			0.049	0.045	0.051	0.048	0.047
			(2.98)**	(2.76)**	(3.08)**	(2.92)**	(2.86)**
DPOSI			-1.001	-0.972	-0.965	-0.982	-0.973
			(-7.02)**	(-6.85)**	(-6.85)**	(-6.94)**	(-6.88)**
NTSALES			0.001	0.001	0.001	0.001	0.001
			(9.52)**	(10.95)**	(17.35)**	(16.74)**	(17.46)**
PURCHASE			0.447	0.444	0.449	0.449	0.446
			(34.95)**	(35.28)**	(36.19)**	(36.18)**	(36.06)**
VWHPRET				-0.021	-0.034	-0.029	-0.023
				(-2.01)*	(-3.21)**	(-2.71)**	(-2.24)*
PFRET0				-3.863			-3.345
				(-17.17)**			(-15.96)**
PFRET1				0.021		0.016	0.024
				(3.42)**		(2.19)*	(3.41)**
PFRET2_5				-0.944		-0.672	-0.732
				(-5.59)**		(-4.03)**	(-4.44)**
PFRET6_20				-0.135		-0.039	-0.061
				(-2.02)*		(-0.68)	(-1.09)
MKTVOL					14.165	12.325	17.348
					(2.35)**	(2.00)*	(2.92)**
MKTRET0					-8.096		-3.248
					(-8.60)**		(-3.43)**
MKTRET1					-10.279	-11.648	-10.234
					(-9.54)**	(-10.54)**	(-9.58)**
MKTRET2_5					-3.187	-2.326	-2.055
					(-6.48)**	(-4.18)**	(-3.84)**
MKTRET6_20					-1.24	-1.082	-1.047
					(-3.77)**	(-3.21)**	(-3.18)**
$\chi^2(1)$	36.06	31.75	46.35	25.33	20.29	23.08	17.02
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Pseudo-R^2	2.79%	2.83%	3.85%	4.02%	4.01%	3.98%	4.11%
Observations	425,749	425,749	425,749	425,598	425,749	425,598	425,598