Essays in Financial Economics: Mental Accounting and Selling Decisions of Individual Investors; Analysts' Reputational Concerns and Underreaction to Public News

DISSERTATION

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ABSTRACT

This dissertation studies how psychological and reputational considerations affect the behavior of individual investors and security analysts. The first essay examines investors' preference for framing their gains and losses using trading records of individual investors at a large discount brokerage firm. I find that investors tend to bundle sales of losers on the same day and separate sales of winners over different days. The result is consistent with the principles of mental accounting (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 winners and losers in a portfolio, the difference in the potential proceeds from selling winners and losers, and correlations among winners and losers in a portfolio 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.

The second essay provides a theoretical and empirical analysis of analysts' incentives to incorporate public information in their earnings forecasts. The model show that analysts may underreact to public news due to their reputational concerns, and that an analyst's incentive to underreact to public information 1) decreases with the size of unexpected news; 2) decreases with the uncertainty of earnings; 3) increases with the analyst's initial reputation; and 4) increases with how much the analyst values his/her current reputation relative to forecast accuracy. I test the implications of the model and find that analysts underreact to earnings news less when the size of unexpected earnings is large, when there is more uncertainty about the earnings, and when they have long track records. The model also implies that the strategic biases of analysts can lead to divergent responses of forecasts to public announcements. Furthermore, the stock market may react to revisions in analysts' forecasts made in response to information that has already been incorporated into stock prices.

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CHAPTER 1

INTRODUCTION

A large body of empirical studies has documented inefficiencies in the behavior of individual investors and security analysts. This dissertation attempts to provide a better understanding of the sources of the inefficiencies by exploring how psychological and reputational considerations play a role in individual investors' trading decisions and security analysts' forecast revisions.

The first dissertation essay, presented in Chapter 2, examines whether individual investors' trading decisions are influenced by a desire to feel good about gains and losses. Because of the diminishing marginal utility of gains and the diminishing marginal disutility of losses in prospect theory (Kahneman and Tversky (1979)), investors attain higher utility by integrating losses and segregating gains. If investors try to frame outcomes in whatever way makes them happiest, they will try to integrate losses and segregate gains (the hedonic editing hypothesis; Thaler (1985)). It is likely that selling stocks on the same day helps investors integrate outcomes; therefore, the hedonic editing hypothesis implies that investors prefer selling losers together and selling winners separately. The results show that investors are more likely to sell multiple stocks on the same day when they realize losses but less likely to do so when they realize gains, consistent with the hedonic editing hypothesis.

Chapter 3 presents the second dissertation essay, which is a theoretical and empirical analysis of analysts' incentives to incorporate public information in their forecasts when they are concerned about their reputations.

In the model, analysts differ in their abilities. A high ability analyst receives more precise private information than a low ability analyst does, therefore puts less weight on public information and makes a smaller revision after public news. Thus, outsiders may infer the ability of the analyst from the amount of revision in response to public news. Outsiders' inferences about the ability of the analyst create incentives for the analyst to underreact to public news.

The model generates testable empirical predictions. The likelihood that an analyst underreacts to public news decreases with the size of unexpected news, decreases with the uncertainty of earnings, increases with the analyst's initial reputation, and increases with the extent to which the analyst values his/her current reputation relative to forecast accuracy. The empirical results generally support the predictions of the model. The model also provides implications regarding several aspects of analyst forecast revisions and their impact on stock prices.

CHAPTER 2

MENTAL ACCOUNTING AND SELLING DECISIONS OF INDIVIDUAL INVESTORS

2.1 Introduction

Recently, researchers have argued that prospect theory (Kahneman and Tversky (1979)) and mental accounting (Thaler (1985)) provide intuitive explanations for many stylized facts about investor behavior and stock returns, such as the disposition effect,[1] the equity premium puzzle (Benartzi and Thaler (1995), Barberis, Huang, and Santos (2001)), the value premium (Barberis and Huang (2001)), and the momentum effect (Grinblatt and Han (2002)). Given the significance of existing and potential future developments along that line, it will be important to examine whether investor trading behavior is consistent with the implications of prospect theory and mental accounting.

This chapter provides a test of prospect theory and mental accounting regarding investors' preferences for framing their gains and losses. In prospect theory, individuals maximize over an "S"-shaped value function. The value function is defined over

[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)

gains and losses and shows diminishing sensitivity to both gains and losses. Mental accounting concerns the way investors evaluate outcomes. 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. Therefore, investors will try to integrate losses and segregate gains if they try to evaluate outcomes in whatever way makes them happiest (the hedonic editing hypothesis; Thaler (1985)).

Thaler and Johnson (1990) assume that choices over the timing of events reflect preferences for integrating or segregating outcomes: It is likely that integration is easier if events occur on the same day and segregation is easier if events occur on different days. Under this assumption, people prefer having events occur on the same day if integration is desired. Similarly, people prefer having events occur on separate 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.

From the trading records of individual investors at a large discount brokerage house during 1991-1996, I find that investors are more likely to bundle sales of stocks that are trading below their purchase prices ("losers") on the same day than stocks are trading above their purchase prices ("winners"). Selling losers on the same day makes it easier for investors to mentally aggregate the losses, and selling winners on different days makes it easier to segregate the gains. Therefore, investors' selling behavior observed in this study can be interpreted as a consequence of their preference for mentally aggregating or segregating events, a preference that is 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 investors might bundle sales of their losing stocks more often than their winning stocks. 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 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 can 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.

I examine each of these alternative hypotheses separately in univariate tests, and also perform multivariate tests which allow simultaneous examination of different determinants of multiple stock sales. The univariate and multivariate tests show that these alternative explanations do not fully account for the finding that investors tend to bundle losses rather than gains on the same day.

As an alternative testing approach, I model the probability of multiple stock sales assuming the selling decision of each stock is independent. Under this assumption, the probability of multiple stock sales increases with the number of winners and 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). The strong empirical evidence on the disposition effect shows that investors' propensity to sell a winner is greater than their propensity to sell a loser. Thus, the impact of an additional winner on the probability of multiple stock sales should be larger than the impact of an additional loser if selling decisions are independent. However, I find the opposite – the effect of an additional loser on the probability of multiple stock sales is much larger than the effect of an additional winner. The result suggests that selling decisions of losers are more positively correlated than selling decisions of winners.

The contributions of the study 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. With the growing body of literature that turns to psychology for a better understanding of the stock market and corporate behavior, tests of psychological theories with the actual behavior of market participants carry important implications.

Second, it complements recent studies on individual investor trading decisions, most of which have examined the decisions for each stock separately.[2] In contrast, this study examines how selling decisions for multiple stocks interact with each other, even in the absence of common fundamental factors.

Finally, the empirical finding of the study may have further implications for equilibrium stock prices. Investors' asymmetric selling decisions for their winners and losers may contribute to the asymmetry in the stock market. For example, empirical

[2]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).

evidence shows that correlations of stock returns are higher in down markets than in up markets.[3] Higher correlations of stock returns in down markets could be due to greater correlations in selling decisions for losers.[4] In addition, investors' selective adoption of different mental accounting systems may affect asset prices. Barberis and Huang (2001) provide a model in which the form of mental accounting affects asset prices in a significant way. If investors prefer integrating their losses and segregating gains, as the results of this study suggest, then mental accounting at the portfolio (individual stock) level will be more prevalent in a down (up) market, implying different market behavior in up and down markets.

2.2 Literature Review

2.2.1 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 and convex for losses, and steeper for losses than for gains.

The value function in prospect theory 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

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

[4]Kyle and Xiong (2001) provide a model where simultaneous liquidation of unrelated securities due to wealth effects leads to financial contagion.

the way investors frame their financial decisions and evaluate the outcomes of their investments.

Thaler (1985) hypothesizes that people try to code outcomes to make themselves as happy as possible. 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 them when segregation yields higher value, $v(x + y) < v(x) + v(y)$. Thaler (1985) derives mental accounting principles that determine whether segregation or integration is preferred ("hedonic editing rules"). The rules characterize decision makers as value maximizers who mentally segregate or integrate outcomes depending on which mental representation is more desirable. The rules prescribe 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 A.1 and A.2). Individuals can maximize their happiness by savoring gains one by one, and minimize the pain by thinking about the overall loss rather than individual losses.[5]

2.2.2 Test of the Hedonic Editing Hypothesis

In principle, individuals could divide gains and combine losses completely arbitrarily in order to maximize 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 experiencing the events on different days when segregation is preferred,

[5] There are four mental accounting principles in Thaler (1985): 1. segregate gains, 2. integrate losses, 3. cancel losses against larger gains, 4. segregate "silver linings" from large losses.

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. Two experimental studies, Thaler and Johnson (1990) and Linville and Fischer (1991), find that people prefer having positive events and also negative events on different days. Thus, the experimental evidence shows only mixed support for the hypothesis. However, these studies are based on responses to questions about hypothetical alternatives, not on the behavior of investors faced with actual investment choices. In contrast, I examine preferences for integrating and segregating outcomes as exhibited in actual trading decisions of individual investors.

Investors realize gains or losses when they sell stocks. Therefore we can draw inferences about investors' preferences for framing gains and losses from how they time sales of stocks. One may argue that a stock 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] Selling a stock makes the outcome seem irreversible. So long as the stock remains in the portfolio, investors can still hope that it will rebound in the future. In addition, selling the stock at a loss 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 principles of mental accounting imply that the pain will be minimized by selling losers at the same time. Similarly, selling a stock at a gain will be registered as a positive event, so

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

people will prefer selling winners on different days to maximize their happiness. The following section lists the main hypothesis and alternative explanations to be tested.

2.3 Hypotheses

The hedonic editing hypothesis implies that investors will try to sell winners on different days and sell losers on the same day so that they can think about the outcomes of their stock investment in more favorable ways. Therefore, I test the following hypothesis:

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 than multiple winners on the same day.

- **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, thus 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 sales of losers because they tend to result in sales of multiple losers rather than sales of multiple winners.

[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).

- **More losers than winners in the portfolio**: The number of stocks that an investor sells largely depends on his opportunity to do so, in other words, on the number of stocks he 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 their portfolios. Thus, the probability of selling multiple losers will be higher than that of multiple winners if investors have more losers than winners in their portfolios.

  It is also 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 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 correlated 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 losers are more likely than winners to be from similar industries, then investors may sell multiple losers on the same day more often than multiple winners.

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

2.4 Empirical Tests

2.4.1 Data Description

The data set of individual investor trades used in this study is from a large 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.

To identify whether each stock is sold at a loss or gain, I compare the price at which the stock is sold with the average purchase price, following previous studies including Odean (1998) and Grinblatt and Keloharju (2000).[8] When there are multiple purchases preceding a sale, the average purchase price is calculated as a split-adjusted share volume-weighted average.[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. I also drop observations 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 A.1 describes the sample of investor trades used in this study. Sales records from a total of 50,229 accounts are examined. 17.2 percent of these accounts 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,

[8]Unlike Odean (1998), commissions are not taken into account in determining whether each stock is sold at a gain or loss. However, the results are much stronger when commissions are added to the purchase price and deducted from the sales price.

[9]The results are similar when the first or the most recent purchase price is used as a reference point.

and sales events from different accounts are treated as different observations.[10] 63.5 percent of the sales events 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 day of stock sales, aggregated over all sales events. I construct investors' portfolios from their purchase records since January 1991 and examine the profile of investor portfolios at the sales event. The median portfolio size and the number of stocks in the portfolio on sales events are $45,406 and 5 for the entire sample. Investors on average have more winners than losers (median number of winners: 3, median number of losers: 2), and the dollar value of a winner is greater than that of a loser (medians are $8,725 and $5,577, respectively).[11]

2.4.2 Proportion of Multiple Stock Sales Conditional on Gains or Losses

Figure A.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 gains and losses for the intervals

[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).

[11]Since portfolios are constructed from the purchase records since 1991, the number of stocks and the portfolio size reported in Table A.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 could have inflated 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.

greater than 5 days, but the difference between them is clearly shown for the interval of 0 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. Figure A.3 illustrates that losses tend to be bundled on the same day compared to gains.

Table A.2 reports the number of sales events separately for gains and losses. To examine whether losses are more likely to be bundled than gains, I classify sales events by whether the sales are at gains or at losses and whether the investor sold multiple stocks on that day. Aggregating a loss with a larger gain is also preferred according to the hedonic editing hypothesis. However, I discard sales events with mixed sales in cross-classification analyses 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 A.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 gains.

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

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

When the events are classified by month, the difference is especially large in December. Investors sell multiple losers in 14.18 percent of the cases and sell multiple winners in 7.93 percent of the cases in December (difference: 6.25 percent). Although the difference between the two proportions is smaller (1.41 percent) from January through November, it remains significant with a t-statistic of 13.82.

Results in Panel C of Table A.2 suggest tax-loss selling is likely to cause clustering of loss selling. It is well known that investors tend to realize their losses near the end of the year to take advantage of tax deductions from capital losses. Therefore, sales of losers from tax-loss selling strategy will be clustered in December. Although the results show that investors are more likely to bundle losses in January through November as well, an alternative way of addressing the tax-loss selling hypothesis is to look at stock sales from retirement accounts (IRA/Keogh), which are either tax-exempt or tax-deferred.

Panel A of Table A.3 documents the results separately for taxable and retirement accounts. As expected, the difference between gains and 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 cannot explain why investors are more likely to sell losers on the same day than winners from their retirement accounts.

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 I examine accounts that allow margin trading and accounts that do not allow margin trading, separately, in Panel B of Table A.3. 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 margin and non-margin accounts, the differences are all significant.

Investors might simply have more losers than winners; therefore, they may sell multiple losers more often than multiple winners. It may also be that a certain group of investors always prefers selling multiple stocks in a day 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 documented in this study could be due to differences in investor characteristics, not because investors prefer integration of losses and segregation of gains.

I control for these possibilities by restricting the sample to those who had the same numbers of winners and losers in their portfolios as of the sales date. This restriction ensures that investors had equal opportunities to sell winners and losers, and also controls for the possibility that differences in the individual characteristics might be driving the results.

To count the number of winners and losers in the portfolio, stocks that are not sold at the sales event are coded as winners or losers based on the closing stock prices on that day. If the closing stock price of the unsold stock is greater than its average purchase price, it is considered a winner. If not, it is considered a loser. A stock that is sold during the day is also coded as a winner if the sales price is greater than the average purchase price and as a loser otherwise.

The results are qualitatively the same under the restriction of equal numbers of winners and losers. In Table A.4, the number of observations is reduced to 64,253 from 400,412 (about 16 percent of the original sample). The difference in the proportions of multiple stock sales is reduced as well (1.64 percent vs. 1.96 percent for the entire sample), but still remains significant. The results in Table A.4 show that investors are more likely to sell multiple stocks when they realize losses even though they had equal opportunities to sell winners and losers. Also, the result rules out the possibility that investor characteristics are solely responsible for the finding.

Because the portfolio is constructed from purchase records since 1991, the number of stocks in the portfolio is downward biased. 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)). Therefore, there might be more losers than winners that are not counted in this analysis because they were purchased prior to 1991. In that case, investors included in the current analysis may actually have more losers than winners because some of their losers were purchased prior to 1991 and therefore not counted. If so, the control of number of stocks could actually bias the results for finding more bundling of losers.

I redo the analysis separately for the sub-periods from 1991 to 1994 and from 1995 to 1996 and report the results in Panel B. The bias from omitted stocks will be minimal in the later part of the sample period.[13] I find that the differences in proportions are pretty similar in two sub-periods, although the difference is slightly

[13]When holding periods are calculated from the round-trip transactions, less than 1 percent of stocks are held for 4 years or longer.

smaller in the later part of the sample period (1.66 percent in the period of 1991-1994, vs. 1.60 percent in the period of 1995-1996).

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 position of each stock in his portfolio. Since the dollar values of losers are on average smaller than the dollar values of winners (Table A.1, Panel C), investors may need to sell more stocks when they sell losers than 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] I address this alternative argument by controlling for the potential proceeds from sales of winners and losers.

For each sales event, I calculate the average dollar value of winners and losers in the investor's portfolio. Panel A of Table A.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), and 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 A.5) when winners and losers have similar dollar values, and the difference is 1.00 percent (t-statistic: 4.74) when losers have larger dollar values than winners. Although the differences are smaller, they are still statistically significant.

[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 the commission charge if they yield the same proceeds.

If losers in a portfolio are more related to each other than 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, or the proportion of losers in similar industries could be greater than that of winners in the same portfolio. I report various measures of relatedness separately for winners and losers based on return correlations and industry membership in Table A.6.

For each sales event, I divide the portfolio from which sales occur 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):

$$RI_k^{\bullet} = \frac{\sum\limits_{i,j \in S_k^{\bullet}, i<j} I_{ij}}{\sum\limits_{i,j \in S_k^{\bullet}, i<j} 1}, \quad CORR_k^{\bullet} = \frac{\sum\limits_{i,j \in S_k^{\bullet}, i<j} \rho_{ij}}{\sum\limits_{i,j \in S_k^{\bullet}, i<j} 1}, \quad MXCORR_k^{\bullet} = \max_{i,j \in S_k^{\bullet}, i<j} \rho_{ij} \quad (2.1)$$

where I_{ij} is an indicator variable equal to 1 if stock i and stock j belong to a same industry, 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, I use two alternative definitions based on 2-digit SIC codes to make sure that the results are not specific to the method 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 $RI(MG)$. After calculating the index of relatedness and the mean and maximum correlations of winner and loser portfolios at the sale event level, I average them across sales events ($N^W(N^L)$ is the total number of winner (loser) portfolios).

$$RI^{\bullet} = \frac{\sum_k RI_k^{\bullet}}{N^{\bullet}}, \quad CORR^{\bullet} = \frac{\sum_k CORR_k^{\bullet}}{N^{\bullet}}, \quad MXCORR^{\bullet} = \frac{\sum_k MXCORR_k^{\bullet}}{N^{\bullet}} \tag{2.2}$$

Table A.6 reports the averages of the indices of relatedness and the averages of mean and maximum correlations of returns for winner and loser portfolios, calculated across sales events. The index of relatedness is higher and the mean and maximum correlations of returns are greater for winner portfolios than loser portfolios, showing that winners are more related to each other than losers.

The indices of relatedness might be 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. It shows that the results are robust in relation to the number of stocks in the portfolios. If some kind of commonality among stocks drives clustering of sales, it should increase the probability of multiple sales of winners rather than losers. Thus, the finding that losers are more likely than winners to be sold on the same day does not seem to be from the greater commonality of losers than winners.

So far, the propensity to sell multiple stocks is calculated by aggregating across sales events from all accounts. Alternatively, I calculate the propensity to sell multiple stocks at an account level in Table A.7. The propensity to sell multiple stocks when the account realizes losses and when it realizes gains, and the difference between them are calculated for each account and then aggregated across accounts.

Let N^i_{lm} (N^i_{ls}) be the number of sales events where account i sells multiple losers (one loser). Similarly, N^i_{gm} (N^i_{gs}) is the number of sales events where 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.

$$DIFF^i = \frac{N^i_{lm}}{N^i_{lm} + N^i_{ls}} - \frac{N^i_{gm}}{N^i_{gm} + N^i_{gs}}\ , \quad DIFF = \frac{\sum_i DIFFi}{\#\ of\ accounts} \tag{2.3}$$

The account level analysis shows results very similar to the aggregated results. On average, the propensity to sell multiple stocks is larger when investors realize losses rather than gains, and the average difference in propensity to sell multiple stocks is 1.96 percent.

2.4.3 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 only one or two controls at a time. I use the following logistic model to examine whether or not realizing losses increases the propensity of investors to sell multiple stocks.

$$Pr(Multi = 1) = \Lambda(\beta_0 + \beta_1 LOSS + \sum_{k=2}^{n} \beta_k x_k + \varepsilon), \tag{2.4}$$

$\Lambda(\cdot)$ is the logistic cumulative distribution function. For each sales event, the dependent variable is a binary variable that takes the value of one if the investor sells multiple stocks, and zero if the investor sells only one stock. $LOSS$ is an indicator variable that takes the value of one if the sales are at losses, 0 if they are at gains, and x_k's are control variables. As in the previous section, I drop sales events in which investors sell both winners and losers.

For the controls, I include a dummy variable for sales events from margin accounts (MARGIN) and a dummy variable for sales events from taxable accounts (TAXABLE), because margin trading and tax-loss selling can contribute to the multiple stock sales. Also included are a dummy for sales in December (DECEMBER), a natural log of the number of stocks in the portfolio (LNSTOCK), 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, $[-5, -2]$, $[-20, -6]$).[15] Other control variables are the average dollar amount position of a stock in the portfolio (DOLLARPOSI), 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). I also include the total number of stock sales from all accounts in the data set on the same day (NTOTSALES) as a proxy for the overall selling activity on that day, and interaction terms of LOSS with a taxable account dummy and a December sales dummy (LOSS*TAXABLE, LOSS*DECEMBER).

Table A.8 reports maximum likelihood estimates of regression coefficients and their robust standard errors. The results in Table A.8 confirm the previous finding

[15]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.

that 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 1 percent level across all models. Since interaction terms of the LOSS variable with the December and Taxable 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*DECEMBER is positive and highly significant. This shows that realizing losses in December increases the multiple stock sales probability, confirming the results in 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 it is 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. The average dollar amount position (DOLLARPOSI) is negatively related to the probability of multiple stock sales, indicating the possibility that investors who sell stocks for liquidity reasons may need to sell multiple stocks if the amount of potential proceeds from selling each stock is small.

Adverse market movements prior to the sales and especially on the sales date increase the probability of multiple stock sales. Investors also appear to be selling multiple stocks in highly volatile markets and on days when there is a high level of selling activity, as the coefficients for MKTVOL and NTOTSALES are positive and significant. Also, the coefficient of the PURCHASE dummy is positive and highly significant. It is possible that sales events with accompanying purchases occur when investors rebalance their portfolios, thus likely to lead to multiple stock sales.

2.4.4 Modeling Stock Sales as Independent Bernoulli Trials

As an alternative approach, I model the probability of observing multiple stock sales if 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, no intentional bundling or separating of sales.

Suppose that whether a stock is sold or not is modeled as an independent Bernoulli trial.[16] 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 her portfolio and the probability that she sells each winner (loser) is p_g (p_l), then the probability of multiple stock sales conditional on sales of any stock is

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

$$= \frac{1 - (1-p_g)^{n_g}(1-p_l)^{n_l} - n_g p_g (1-p_g)^{n_g - 1}(1-p_l)^{n_l} - n_l p_l (1-p_g)^{n_g}(1-p_l)^{n_l - 1}}{1 - (1-p_g)^{n_g}(1-p_l)^{n_l}}, \tag{2.5}$$

where n_s is the number of stocks that she sells.

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

Figure A.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 $p_l = 0.098$.[17] It shows that the logit of the probability of multiple stock sales increases with n_g and 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 the investor's propensity to sell a winner is greater than the propensity to sell a loser ($p_g > p_l$).

Suppose we estimate the following logit model:

$$Pr(Multi = 1) = \Lambda(\alpha + \beta_g n_g + \beta_l n_l + \varepsilon) \tag{2.6}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function, equivalent to modeling logit of $Pr(Multi = 1)$ as a linear function of n_g and n_l. The estimated coefficients for the number of winners (β_g) and for the number of losers (β_l) are related to the propensities to sell a winner and a loser. If we believe that investors are less likely to sell a loser than a winner 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 $\beta_g < \beta_l$, it 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, thus reversing the relationship between these two coefficients.

[17] I chose p_g and p_l based on the results of Odean (1998).

Table A.9 estimates the following model:

$$Pr(Multi = 1) = \Lambda(\alpha + \beta_g n_g + \beta_l n_l + \sum_{k=1}^{n} \beta_k x_k + \varepsilon), \tag{2.7}$$

where x_k's are control variables similar to those used in Table 8. The specification allows for bundling gains and losses; therefore, I include the mixed sales in this analysis.

Table A.9 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 those two coefficients reject the null hypothesis ($H_0 : \beta_g = \beta_l$) at the 1 percent level.

If we believe that there is no dependency in sales 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 shows that each loser is less likely to be sold than a winner ($p_l < p_g$). Therefore, the results in Table A.9 provide further evidence that selling decisions for losers are more correlated with each other than the selling decisions for winners.

2.5 Discussion

This paper focuses on one of the implications of prospect theory and mental accounting that individuals achieve higher utility by integrating losses and segregating gains. This implication generates a testable hypothesis on investor trading behavior as examined in this paper, and is also 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 hedonic framing 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 in the IPOs. They argue that the loss from underpricing will be aggregated with a larger gain from the retained shares, therefore issuers will 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.[18] 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.[19] Mental accounting of multiple outcomes based on prospect theory provides an alternative explanation for the coexistence of these seemingly opposite behaviors. If investors have preferences consistent with the prospect theory value function, 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

[18]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 by September 1998 were up 83 percent. The 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)

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

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.

2.6 Conclusion

With the rapid growth of behavioral models that incorporate findings from psychology in their assumptions, it becomes more important to test the underlying behavioral theories with the data of actual decisions made by market participants.

This paper tests one of the implications of prospect theory and mental accounting by examining whether individual investors time the sales of losers differently from the sales of winners. The results show that investors tend to sell losers on the same day, while they tend to sell winners on different days. The tendency of investors to realize multiple losses on the same day and gains over different days can be interpreted as a result of their preference for integrating losses and segregating gains implied by the hedonic editing hypothesis (Thaler (1985)).

I explore several alternative explanations that are based on tax-loss selling strategies, margin calls, the number of losers and winners in the portfolio, difference in the potential proceeds from selling winners and losers, and correlations of winners and losers. These alternative explanations do not fully account for the observed behavior.

The results show how selling decisions for multiple stocks interact with each other, complementing other recent studies on individual investor trading behavior. In addition, the results help us understand how investors perform mental accounting of their investments. As Barberis and Huang (2001) show, the nature of investors' mental accounting affects empirical predictions about the equilibrium asset prices. Thus, identifying which mental accounting system is used by investors can help us better understand asset prices.

CHAPTER 3

ANALYSTS' REPUTATIONAL CONCERNS AND UNDERREACTION TO PUBLIC NEWS

3.1 Introduction

This chapter examines how the reputational concerns of analysts influence the extent to which their earnings forecasts incorporate public information. Many studies have documented that analyst forecasts underreact to publicly available information such as past earnings and past stock prices. However, relatively few studies have explored the underlying causes of analysts' underreaction. I show that analysts may not fully revise their forecasts after the arrival of public news, derive conditions under which such underreaction to public information occurs, and test the implications of the model by relating the degree of analysts' underreaction to the size of earnings news, the extent of earnings uncertainty, and the characteristics of individual analysts. The model also provides further implications regarding analysts' forecast revisions and their impact on the stock market.

The model focuses on the decisions of an analyst regarding how much to revise the forecast when public information arrives. In the model, the analyst is concerned about her reputation, so her forecast is set strategically and may differ from the true expectation of the analyst. Before public information arrives, the analyst bases her forecast on her private information. After observing a public signal, the expectation of the analyst about future earnings is revised as a weighted average of the previous forecast and the public signal, where the weights are determined by the relative precision of private and public information.

In the model, the analyst has private information about her ability, which is measured by the precision of her private information. The analyst is one of two types, high or low ability. A high ability analyst receives more precise private signals than a low ability analyst. Because high and low ability analysts put different weight on private information, they revise differently in response to public information. A high ability analyst puts less weight to public information than to the private information, therefore has a weaker propensity to revise the forecast than a low ability analyst. Thus, outsiders may infer the type of the analyst from the amount of revision after a public news release. Given such inference, a low ability analyst has an incentive to mimic a high ability analyst, while a high ability analyst wants to avoid such mimicry. Therefore, for both reasons, the inference about the type of the analyst through revisions around public news creates incentives for the analyst to underreact to the public news.

The model not only gives us insights about why there might be an underreaction to public information but also provides empirical predictions, some of which have not been previously tested. I show that, for certain realizations of the public signal, there is an equilibrium in which analysts underreact to public news, and that the probability of an analyst underreacting to public information 1) decreases with the size of unexpected news, 2) decreases with the uncertainty of earnings, 3) increases with the initial reputation of the analyst, and 4) increases with how much the analyst values short-term reputation relative to forecast accuracy.

The model also provides implications regarding several aspects of analysts' forecast revisions and their impact on the stock market. It shows that analysts' strategic bias may lead to divergence in forecasts after public announcements, and that the stock market may react to analysts' revisions which are based on the information that has already been incorporated into stock prices.

In the empirical test, I find that the degree of analysts' underreaction, as measured by the estimated coefficient from a regression of forecast errors on their previous forecast errors, is greater when the size of unexpected news (or earnings surprise) is small, when there is less uncertainty about earnings, and when the analyst have a short track record. These results are consistent with the predictions of the model. On the other hand, I find that the past forecast accuracy of the analyst is negatively related to the degree of underreaction. If the past forecast accuracy of an analyst proxies for the initial reputation of the analyst, this is inconsistent with the prediction about the effect of the initial reputation on the degree of underreaction. However, unlike other predictions of the model, this prediction holds only for a special case in which the difference in the ability of a high and a low type analyst is constant.

3.2 Literature Review

3.2.1 Evidence of Analysts' Underreactions

It is well documented that security analysts underreact to publicly available information. For example, analysts underreact to past earnings information[20] and past

[20] E.g, Mendenhall (1991), Abarbanell and Bernard (1992), Ali, Klein, and Rosenfeld (1992), Jacob and Lys (2000), Raedy and Shane (2000), Shane and Brous (2001).

stock prices.[21] Analyst forecast error is also predictable from prior revisions,[22] suggesting that analysts underreact to more general information. The evidence of underreaction is not unique to security analysts. For example, Batchelor and Dua (1992) find that economic forecasters are conservative in making forecast revisions, and that forecasters put too little weight on the known forecasts of other forecasters.

Similar underreaction is also observed in the stock market. Bernard and Thomas (1990) and Freeman and Tse (1989) present evidence that the stock market underestimates the implications of previous earnings for future earnings (post-earnings announcement drift). Abarbanell and Bernard (1992) and several other studies examine whether analysts' underreaction to prior earnings information can explain the post earnings announcement drift. While Abarbanell and Bernard (1992) conclude that analysts' underreaction can be only a partial explanation for stock price underreaction to earnings, more recent studies present evidence that the extent to which analysts' behavior can explain the market underreaction might be greater. Shane and Brous (2001) show that incorporating the market's correction of underreaction in response to non-earnings surprise information significantly increases the estimates of the degree to which analysts' forecasts can explain post-earnings announcement drifts. Using an intrinsic value measure based on analysts' short- and long-term earnings forecasts, Liu (1999) finds that analysts underreact to earnings news more than the stock market.

Post-earnings announcement drift is a well-known anomaly in the stock market. If post-earnings announcement drift is related to analysts' underreactions to earnings

[21] E.g., Klein (1990), Lys and Sohn (1990), Abarbanell (1991) .

[22] Elliott, Philbrick, and Wiedman (1995), Amir and Ganzach (1998), Easterwood and Nutt (1999)

news, possibly through investors' reliance on their forecasts, it is important to determine what the underlying causes of analysts' underreactions. However, relatively few studies have attempted to identify the determinants of analysts' underreactions.

Jacob and Lys (2000) find that analysts exhibit similar patterns of serial correlations in forecast errors across all the companies they follow, and that analysts following the same company also show similar patterns of serial correlation. These findings suggest that there are analyst- and company-specific factors underlying analysts' underreactions. Mikhail, Walther, and Willis (2001) show that the degree to which analysts underreact to past earnings news decreases with their experience, possibly because cognitive biases that lead to underreactions are mitigated with experience.

While these earlier studies examined the determinants of analysts' underreaction empirically, this paper identifies them theoretically and brings them to empirical tests. The model shows why analysts' underreaction tends to be analyst- and firm-specific, and suggests that the finding of Mikhail, Walther, and Willis (2001) could also be due to analysts' reputational concerns, which are likely to be greater among younger analysts.

3.2.2 Is Underreaction of Analysts Intentional?

Inefficient processing of information due to psychological biases such as conservatism (Edwards (1968)) and overconfidence (e.g., Griffin and Tversky (1992)) can result in underreaction.[23] But even when analysts are free of psychological biases

[23]Friesen and Weller (2002) develop a model of analyst earnings forecasts that discriminates between rational behavior and that induced by cognitive biases, and find that analysts are overconfident about the precision of their own information. But they do not consider the possibility that analysts may issue biased forecasts strategically.

and are able to process information in an efficient and unbiased way, they may have incentives to report forecasts that differ from their expectations about earnings.

Analysts may issue optimistic forecasts to gain access to inside information from managers, for example, to win investment banking business.[24] The incentives to report optimistic forecasts to maintain management relations are stronger when there is negative information (Francis and Philbrick (1993)), which could be one explanation for underreactions, especially to negative information.

Analysts also care about their reputations because one's professional regard affects one's current and future wages. Outsiders learn about analysts' abilities through the observable data – their forecasts. Analysts may not truthfully report their expectations of earnings if doing so adversely affects their reputations. This paper focuses on analysts' incentives to influence outsiders' assessments about their abilities as a possible explanation for their underreactions to public news.

It is somewhat surprising that Liu (1999) finds analysts underreact more than investors. Analysts are trained to analyze financial data, and they have industry expertise as well as detailed firm-specific knowledge through contacts with managers. We therefore expect analysts to be better than average investors at forming expectations based on available information. If the underreactions of analysts are due to their strategic biases, investors can undo the bias (at least partly) and underreact less than analysts do. Therefore, Liu's (1999) finding suggests that analysts' underreactions may derive from their strategic biases, possibly due to their reputational concerns.

[24]See, e.g., Das, Levine, and Sivaramakrishnan (1998), Dugar and Nathan (1995), Francis and Philbrick (1993), Hong and Kubik (2003), Lim (2001)

3.2.3 Reputational Concerns and Underreaction to Information: Theories

Trueman (1990) shows that an analyst may be reluctant to revise a previously issued forecast upon receipt of new information. Forecast revision implies that the analyst's original information was inaccurate, and thus investors will lower their assessment of the analyst's ability to collect information in a timely manner.

In his model, an analyst can receive private information at an earlier date (date-1) or a later date (date-3), or never. The compensation for the analyst increases with the probability that the analyst receives private information at date-1. As a result, an analyst who did not receive a private signal at date-1 acts as if she received it, revises at date-2 upon public information as if her date-1 forecasts were based on private information that she actually did not receive. If private information arrives at date-3, she may not revise since revision at date-3 indicates she did not receive private information at date-1. To appear as analysts who receive private information early, analysts underreact to subsequent public and private information.[25]

Prendergast and Stole (1996) examine how individuals change their behavior on receipt of new information when they wish to acquire a reputation as fast learners, where the learning ability is reflected in the precision of their private signal. In the context of a manager making investment decisions on projects over time based on his private information, they show that the manager first exaggerates his private information but later becomes too conservative. Since a talented manager puts more weight on the private information, his posterior belief is more variable than that

[25] Although he modelled analyst's ability as related to the timing of private signal arrival, it can also be stated in terms of the precision of the date-1 signal. Not observing a private signal at date-1 is equivalent to receiving a signal that is uninformative (zero-precision).

of an untalented manager. Thus, a manager wants to exaggerate his true belief at the beginning of his career. But he acts conservatively later on because changes in decisions become associated with his previous errors. Also, managers always act conservatively to public information whose precision does not depend on ability.

The basic insight presented in this study is similar to that of Trueman (1990) and Prendergast and Stole (1996): reputational concerns create incentives for agents to underreact to information. This paper contributes to the existing literature by deriving empirical predictions on the determinants of analysts' underreactions to public news, which can be easily tested by examining how analyst and event characteristics are related to the degree of analysts' underreactions. The model also offers alternative explanations regarding why forecasts might diverge after the release of public news and why the stock market may react to analysts' forecasts which are revised based on the information that is already known to investors.

3.3 The Model

3.3.1 The Economic Setting

Let e denote a firm's earnings, distributed normally with mean zero and variance $1/\nu_0$. At $t = 1$, an analyst receives a private signal s_1 about the earnings,

$$s_1 = e + \epsilon_1, \tag{3.1}$$

where $\epsilon_1 \sim N(0, 1/\nu_1)$ and is independent of e. After observing a private signal, the analyst updates her belief about e and issues the first-period forecast F_1. At t=2, the analyst receives a public signal s_2, where

$$\begin{aligned} s_2 &= e + \epsilon_2, \\ \epsilon_2 &\sim N(0, 1/\nu_2), \end{aligned} \tag{3.2}$$

and issues the second-period forecast F_2 based on the private and public signal. Figure A.5 summarizes the sequence of events.

An analyst is either of high (H) or low (L) ability. The analyst knows her own ability, but outsiders do not. Before date-1, outsiders only know that an analyst's ability can be either high or low with a probability μ_0 and $1 - \mu_0$, respectively. For an analyst of type $\Theta \in (H, L)$, the precision of the date-1 private signal is ν_1^Θ. A high ability analyst receives a more precise private signal ($\nu_1^H > \nu_1^L$).

3.3.2 Analyst's Forecast Revision After Public News

If the analyst tries to minimize the mean-squared forecast error, her forecast should be the expectation of earnings conditional on the available signal(s),

$$\begin{aligned}
F_1 &= E[e|s_1] = \left(\frac{\nu_1^\Theta}{\nu_0 + \nu_1^\Theta}\right) s_1 \\
F_2 &= E[e|s_1, s_2] = \left(\frac{\nu_2}{\nu_0 + \nu_1^\Theta + \nu_2}\right) s_2 + \left(\frac{\nu_1^\Theta}{\nu_0 + \nu_1^\Theta + \nu_2}\right) s_1 \\
&= F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^\Theta + \nu_2}\right)(s_2 - F_1). \qquad (3.3)
\end{aligned}$$

The forecast revision, $F_2 - F_1$ is then

$$F_2 - F_1 = \left(\frac{\nu_2}{\nu_0 + \nu_1^\Theta + \nu_2}\right)(s_2 - F_1). \qquad (3.4)$$

Since outsiders also observe the date-2 public signal s_2 and the analyst's date-1 forecast F_1, they can perfectly infer the analyst's ability ν_1^Θ from the forecast revision $F_2 - F_1$ if the analyst reports the date-2 forecast truthfully. The high ability analyst will revise less, holding other things constant. Therefore, reputational concerns can distort the forecasts because the analyst wants to appear as a high type.

For tractability, I assume that the first-period forecast F_1 is the analyst's true conditional expectation of e.[26]

$$\begin{aligned} F_1 &= \left(\frac{\nu_1^\Theta}{\nu_0+\nu_1^\Theta}\right)s_1 \\ F_1 &\sim N(0, \frac{\nu_1^\Theta}{\nu_0(\nu_0+\nu_1^\Theta)}) \end{aligned} \tag{3.5}$$

Since the private signal s_1 is not observable, outsiders cannot infer from F_1 whether the analyst is a high or low type.[27] They only update their belief about the analyst's type after observing the date-1 forecast F_1. The probability that the analyst is a high type when the date-1 forecast is F_1 is

$$\begin{aligned} \mu \equiv Pr(\Theta = H|F_1) &= \frac{Pr(\Theta = H)Pr(F_1|\Theta = H)}{Pr(\Theta = H)Pr(F_1|\Theta = H) + Pr(\Theta = L)Pr(F_1|\Theta = L)} \\ &= \frac{\mu_0 Pr(F_1|\Theta = H)}{\mu_0 Pr(F_1|\Theta = H) + (1-\mu_0)Pr(F_1|\Theta = L)}, \end{aligned} \tag{3.6}$$

where

$$Pr(F_1|\Theta) = \frac{1}{\sqrt{2\pi\sigma_\Theta^2}}e^{-\frac{F_1^2}{2\sigma_\Theta^2}}, \quad \sigma_\Theta^2 \equiv \frac{\nu_1^\Theta}{\nu_0(\nu_0+\nu_1^\Theta)}. \tag{3.7}$$

Suppose that the analyst's objective at $t = 2$ is to maximize the weighted sum of the forecast accuracy and outsiders' assessment of the analyst's ability, $\hat{\nu_1}$.

[26]The analyst will issue her date-1 expectation of e truthfully if the date-1 objective of the analyst is to minimize the mean-squared error of the date-1 forecast. In a dynamic setting, the analyst would like to adjust her date-1 forecast in anticipation of the strategic game at date-2. For her reputation, the analyst wants to report F_1 that minimizes the future revision because larger revision signals lower ability. However, $F_1 = E[e|s_1] = \nu_1^\Theta s_1/(\nu_0+\nu_1^\Theta)$ is an unbiased estimator of e and also of the date-2 signal given s_1. Since the analyst can minimize date-2 revision by issuing an unbiased estimator of e, reporting F_1 is the best strategy even in a dynamic setting where the analyst's date-1 concern is the inference about her ability at date-2. When outsiders believe that the analyst's date-1 forecast is a true conditional expectation of e, it is indeed optimal for the analyst to report truthfully at date-1. However, if the analyst is concerned about her date-1 reputation as well, truthful reporting is no longer optimal. A numerical example is presented in Appendix B where the date-1 objective is to maximize a weighted sum of forecast accuracy and date-1 reputation. In such case, there is an overreaction to date-1 private information and underreaction to date-2 public information.

[27]Even when F_1 is strategically biased, it is not possible for outsiders to infer the analyst's type perfectly at date-1.

Then the analyst solves

$$\max_{F_2} -E[(e - F_2)^2] + \lambda \hat{\nu_1}, \tag{3.8}$$

where λ is the weight on the outsiders' assessment about the analyst's ability.

Proposition 1 *There are three possible equilibria at date 2.*

1. A separating equilibrium where each type reports the conditional expectation of the earnings truthfully,

$$F_2^\Theta = F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^\Theta + \nu_2}\right)(s_2 - F_1), \quad \Theta \in (H, L). \tag{3.9}$$

2. A separating equilibrium where a high type analyst reports a forecast that does not fully incorporate the public signal to separate from a low-type,

$$\begin{aligned} F_2^H &= F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2} - \frac{\sqrt{\lambda(\nu_1^H - \nu_1^L)}}{|s_2 - F_1|}\right)(s_2 - F_1) \\ F_2^L &= F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}\right)(s_2 - F_1). \end{aligned} \tag{3.10}$$

3. A pooling equilibrium where both high and low types revise in the same way.

$$F_2^\Theta = F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2}\right)(s_2 - F_1), \quad \Theta \in (H, L). \tag{3.11}$$

The high-type reports the true conditional expectation of e, and the low-type under-adjusts its forecast to mimic the high-type. This equilibrium is supported by the out-of-equilibrium belief in which those who deviate from the equilibrium are considered the low-type.

Depending on the realization of s_2, there is either a unique equilibrium or multiple equilibria at date 2. Let $K \equiv \sqrt{\lambda}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)/\nu_2\sqrt{\nu_1^H - \nu_1^L}$.

- *When* $|s_2 - F_1| \geq K$*, the unique equilibrium is Equilibrium 1 where both types report truthfully.*

- *When* $\sqrt{\mu}K < |s_2 - F_1| < K$*, the unique equilibrium is Equilibrium 2 where the high type separates itself from the low type by reporting a biased forecast.*

- *When* $|s_2 - F_1| \leq \sqrt{\mu}K$*, there are two possible equilibria. One is the separating equilibrium where the high type separates itself from the low type by reporting a biased forecast (Equilibrium 2), and the other is the pooling equilibrium where both types revise in the same way (Equilibrium 3).*

Proof of Proposition 1: see Appendix B

In Equilibria 2 and 3, a certain type of analyst underreacts to public news. In the pooling equilibrium (Equilibrium 3), a low ability analyst under-adjusts for the public information to pool with a high ability analyst, and in the second separating equilibrium (Equilibrium 2), a high type analyst under-adjusts to separate herself from a low ability analyst.

From the range of s_2 for each equilibrium listed in Proposition 1, I derive comparative statics. (*Proof of Corollary 1: see Appendix B.*)

Corollary 1 *The probability that the analyst underreacts to public information at date 2*

1. *decreases with* $|s_2 - F_1|$,
2. *increases with* ν_0,
3. *increases with* λ,
4. *increases with* $\bar{\nu}_1 \equiv \mu\nu_1^H + (1-\mu)\nu_1^L$*, if the dispersion in ability,* $\nu_1^H - \nu_1^L$*, is constant.*

There is an underreaction to public information in Equilibria 2 and 3, either because the low type is trying to mimic the high type, or because the high type is trying to separate itself from the low type. The range of s_2 for those equilibria is:

$$|s_2 - F_1| \leq \frac{\sqrt{\lambda}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)}{\nu_2\sqrt{\nu_1^H - \nu_1^L}}. \tag{3.12}$$

Ex post, there is an underreaction when the size of the unexpected news, $|s_2 - F_1|$, is small. Ex ante, the probability that the value of the public signal s_2 satisfies the condition (3.12) increases with the inverse of earnings uncertainty (ν_0), the weight the analyst puts on the current reputation (λ), and the initial reputation of the analyst ($\bar{\nu}_1$) if $\nu_1^H - \nu_1^L$ is constant.

When ν_0 is large, the analyst holds a tight prior about the earnings, thus her belief about future earnings does not change much after the public news. This implies that the cost of underreaction to public news is small, and therefore the anlayst is more likely to underreact to public information.

The prediction about $\bar{\nu}_1$ is also related to the impact of public information on the belief revision. When a private signal is more accurate, there is less need to revise upon public information. The analyst balances the costs of inaccurate forecasts with the possible reputational gains from underreacting to public news. The cost of underreaction will be smaller as the public news becomes less important relative to the prior belief, which is formed by the private signal and the prior on earnings distribution. As such, the analyst is more likely to underreact to public information when ν_0 and $\bar{\nu}_1$ are large, due to smaller importance of public information.

$\bar{\nu}_1$ can be interpreted as an initial reputation of an analyst. In a model of investment advisor herding, Graham (1999) shows that the incentive for the second-mover to herd increases with his initial reputation. When the initial reputation is high, he has 'farther to fall,' and therefore more likely to herd to preserve his reputation.[28]

The prediction about the effect of the initial reputation on analysts' inefficient behavior is similar to Graham's, but through a different mechanism. The 'degree to fall' is captured in the difference in the ability, which is held constant when I derive the prediction about $\bar{\nu}_1$. The higher the initial ability, the less they put weight on public information. Lower importance of public information implies that the cost of underreaction to such information will be lower, making strategic bias to influence outsiders' perception of their ability more attractive.

Corollary 2 *When $\nu_2|s_2 - F_1|/(\nu_0 + \nu_1^L + \nu_2) < \sqrt{\lambda(\nu_1^H - \nu_1^L)}$, a high type and a low type analyst may react to a given public signal realization in opposite directions.*

Corollary 2 implies that public news may lead to divergence in forecasts. In Equilibrium 2, the high type chooses date-2 forecast by adding a constant bias to the low type's forecast, where the amount of bias is equal to the low type's reputational gain from mimicking the high type and the direction of the bias is opposite of the low type's revision. If the amount of bias is greater than the low type's revision, the revision of the high type will be in the opposite direction of the low type's. In such case, analysts of different types react to public signal in opposite directions, creating divergence of forecasts after the public news.

Kandel and Pearson (1995) find that analysts' forecast revisions around quarterly earnings announcements show divergence and flips, which should not be observed if agents interpret public information identically. They suggest that it could be due

[28]He interprets the probability that an analyst is smart as an initial reputation, which he separates from the *ability* which is the signal precision of a smart analyst. In the model of this paper, the sign of the comparative statics with respect to ν_1^H is ambiguous.

to the different likelihood functions agents use. Kim and Verrecchia (1994) point that financial accounting disclosures can induce increased information asymmetry, less liquidity, and more trading volume because market participants process earnings announcement into possibly diverse information by informed judgement.

The result here offers an alternative explanation for the divergence in analyst forecasts after public news. Analysts interpret public information identically therefore their expectations do not diverge, but their reported forecasts can diverge due to strategic bias.

3.3.3 Stock Market Reaction to Forecast Revisions

Lys and Sohn (1990) find that analyst forecasts are informative even when they are preceded by earnings forecasts made by other analysts or by corporate accounting disclosures. Stickel (1991) also documents that abnormal returns following forecast revisions occurring within a few days of corporate announcements (earnings, dividend, and stock-split announcements) are as significant as those following revisions not confounded by corporate announcements. This implies that the information in the revisions that are triggered by corporate announcements goes beyond the information contained in the announcements.[29]

The model shows that forecast revisions after public news lead to further stock market movements, even though forecasts are revised solely based on the public information which is already available to other market participants. Forecast revisions

[29] Similar results are found in analysts' recommendations. Park and Pincus (2000) examine whether analysts' recommendations made within five days following earnings announcements convey information beyond that reflected in earnings announcement, and find that it is the case. They argue that it is consistent of the capital market viewing analyst recommendation revisions as reflecting valuable expertise to process and interpret public signals.

contain information about the type of analysts and therefore about the informativeness of their pre-existing forecasts. Thus, the stock market reacts to the forecast revisions even though analysts are responding to the information that is already incorporated in the stock prices.

To clarify the timing of events, let us break date-2 into two parts. At $t = 2^-$, outsiders (stock market) and the analyst receive public signal s_2 and both form expectations of the earnings based on available information. At $t = 2^+$, the analyst announces her revised forecast F_2 and outsiders may update their belief about the earnings after observing the analyst's revision. It captures the lag between the arrival of public information and reporting of the analyst's revised forecasts (see Figure A.6).

Let us assume that the stock price is equal to the market's expectation of the earnings. At $t = 2^-$, outsiders' belief about the earnings is based on the analyst's date-1 forecast and the public signal s_2.[30] Since they do not know the type of the analyst at that point, the weight they put on the public signal is a weighted average of two possible weights – a weight that a low type analyst would put on the public news and a weight that a high type would. The stock price at $t = 2^-$, $P_{t=2^-}$, is

$$P_{t=2^-} = E^M[e|F_1, s_2] = F_1 + \left[\mu \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2}\right) + (1-\mu)\left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}\right)\right](s_2 - F_1), \tag{3.13}$$

where μ is the probability that the analyst is a high type, as defined in equation (3.6).

After the analyst reports F_2, the market can infer the type of analyst from her revision under a separating equilibrium, which is possible for all parameter range. When investors infer the analyst's type Θ from the date-2 forecast $F_2 = F_2^\Theta$, they

[30] The analysis assumes that there is only one analyst following a particular company. But the intuition developed here still holds in more general setting where there are multiple analysts following the firm.

revise the weights on the analyst's existing forecast and the public news.

$$P_{t=2^+} = E^M[e|F_1, s_2, F_2^\Theta] = F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^\Theta + \nu_2}\right)(s_2 - F_1) \tag{3.14}$$

The stock market reaction to the analyst's revision is

$$\begin{aligned}
\Delta P &= P_{t=2^+} - P_{t=2^-} \\
&= \left[\left(\frac{\nu_2}{\nu_0 + \nu_1^\Theta + \nu_2}\right) - \mu\left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2}\right) - (1-\mu)\left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}\right)\right](s_2 - F_1) \qquad (3.15) \\
&= \begin{cases} -(1-\mu)\left(\frac{\nu_2}{\nu_0+\nu_1^L+\nu_2} - \frac{\nu_2}{\nu_0+\nu_1^H+\nu_2}\right)(s_2 - F_1), & \text{when} \quad F_2 = F_2^H \\ \mu\left(\frac{\nu_2}{\nu_0+\nu_1^L+\nu_2} - \frac{\nu_2}{\nu_0+\nu_1^H+\nu_2}\right)(s_2 - F_1), & \text{when} \quad F_2 = F_2^L \end{cases}
\end{aligned}$$

If investors find that the analyst is a high type, they realize their previous reaction to the public news at $t = 2^-$ was too large because they did not put enough weight on the analyst's date-1 forecast. Thus, they correct their previous overreaction to the public news by reacting in opposite direction of public news $(s_2 - F_1)$. On the other hand, if investors realize that the analyst's ability is lower than what they previously thought, their reaction to the analyst's revision shows continuation from their previous reaction to the public news.

When investors lower their assessment of the analyst's ability after observing the analyst's revision, they decrease the weight on the analyst's pre-existing forecast and increase the weight on the public news. For example, a large, upward forecast revision following a positive public news will result in further positive stock price movements. It is not because the revision brings more positive news to the market, but because it indicates that investors should lower the weight they put on the analyst's previous forecast and increase the weight on the public news.

The fact that forecast revisions are informative does not necessarily mean that the revisions are based on new information that has not been available to investors. Forecast revisions may convey information about the quality of the *pre-existing* forecasts and lead to further market reactions, even when they are based on the information that has already been incorporated into the stock prices.

The result also has implications on the relationship between the forecast revision $F_2 - F_1$ and the stock market reaction to the revision ΔP. Since large revisions are associated with a low ability analyst, market reacts in the same direction as the analyst's revision for large revisions. Thus, the relation between the stock price change ΔP and the forecast revision $F_2 - F_1$ will be positive on average conditional on the sign of the revisions.

The following proposition summarizes these results.

Proposition 2 *Suppose an analyst revises the forecast in response to public news and the revised forecast is announced after the news is fully incorporated into the stock price. Then the announcement of the revised forecast may lead to further stock market reaction.*

1. For larger revisions (which are associated with the low ability analyst), the market reacts in the same direction as the previous reaction to the public news.

2. For smaller revisions (which are associated with the high ability analyst), the market reacts in the opposite direction of the previous reaction to the public news.

3.4 Empirical Tests

3.4.1 Test Design

The comparative static results from the model suggest that the analyst is more likely to underreact to public information when:

- the magnitude of the *surprise* in public news is small,
- there is less uncertainty about the earnings,
- the analyst has greater reputational concerns,
- and the analyst has a better initial reputation.

If analysts underreact to public news, their forecast errors are predictable from the content of the public news. Positive news will be followed by positive forecast errors (earnings minus forecasts) and vice versa for negative news.

I choose the quarterly earnings announcements as the public news events for the following reasons. First, earnings announcements are probably the most important public announcements for earnings forecasters. Forecast revisions are concentrated within a few days of earnings announcements,[31] indicating the importance of prior earnings information for the analysts. Second, analysts' and investors' underreactions to earnings information have been the focus of numerous studies and still remains a puzzle (see Section 3.2.1 for a review).

I assume that the degree of underreaction to the earnings news can be measured by the regression coefficient β_j of the following regression.

$$e_{j,q} - F_{i,j,q} = \alpha_j + \beta_j(e_{j,q-1} - F_{i,j,q-1}) + \varepsilon_{i,j,q} \tag{3.16}$$

[31] Cooper, Day, and Lewis (2001) document that about 25% of annual earnings forecasts were released within a five-day window surrounding the quarterly earnings announcements.

$e_{j,q}$ is the actual earnings of the firm j for the quarter q and $F_{i,j,q}$ is the forecast of analyst i for the earnings of the firm j for the quarter q. $(e_{j,q-1} - F_{i,j,q-1})$ is the forecast error of the previous quarter – the surprise part of the information in the previous quarter's earnings announcement. Underreaction to prior earnings information implies that $\beta_j > 0$.[32]

To control for the cross-sectional differences in the implications of prior earnings news on the current period's earnings, I estimate the regression at a firm level and then report the mean regression coefficient estimates and corresponding $t-$ and $Z-$statistics.

The model predicts that the degree of underreaction will depend on various parameters. Thus, I model α_j and β_j as linear functions of variables that proxy for the parameters in the model.

$$e_{j,q} - F_{i,j,q} = \alpha_j(\boldsymbol{Z}_{i,j,q}) + \beta_j(\boldsymbol{Z}_{i,j,q})(e_{j,q-1} - F_{i,j,q-1}) + \varepsilon_{i,j,q} \tag{3.17}$$

where $\boldsymbol{Z}_{i,j,q}$ is a vector of variables (including constant) that proxy for the earnings uncertainty $(1/\nu_0)$, the analyst's initial reputation $(\bar{\nu}_1)$, the degree of the analyst's reputational concerns (λ), and the size of unexpected news $(|s_2 - F_1|)$. The specification allows me to examine how the degree of underreaction, β_j, varies with the analyst's characteristics, earnings uncertainty, and the magnitude of the earnings surprise.

[32] A number of papers interpreted β_j as a measure of the degree of underreaction (e.g., Abarbanell and Bernard (1992), Amir and Ganzach (1998)), Mikhail, Walther, and Willis (2001)). I derive conditions under which underreaction occurs, not the extent of the underreaction. But the model provides general intuitions on when analysts have greater incentives to underreact to public information.

3.4.2 Data Description

Using data from the period 1984-2001, I test the predictions of the model using analysts' one-quarter ahead forecasts that are revised after the earnings announcements from the previous quarter. Individual analyst forecasts, forecast publication dates, and the actual earnings per share (EPS) are from the Institutional Brokers Estimate System (I/B/E/S) detail history tape. Forecast errors are calculated using the actual earnings from I/B/E/S instead of earnings from COMPUSTAT, since I/B/E/S actual earnings are recorded on the same basis on which analysts report their forecasts. Stock prices and daily returns are provided by Center for Research in Security Prices (CRSP), and quarterly earnings announcement dates are obtained from COMPUSTAT.

Forecast errors (FE: Earnings - Forecasts) are deflated by the stock price at the beginning of the quarter. To control for outliers and possible data entry errors, I delete observations with stock prices less than \$5, or with absolute forecast errors before deflation that are greater than \$10 per share.[33] I then winsorize the deflated forecast errors to 0.1 following previous studies.[34]

I use the following proxies for the parameters in the model.

- The magnitude of unexpected news ($|s_2 - F_1|$)

  In this empirical test, I examine analysts' underreaction to the earnings announcements for the previous quarter. Since the public news events used in the empirical tests are quarterly earnings announcements, the magnitude of the

[33] O'Brien (1988), Lim (2001), Bernhardt, Campello, and Kutsoati (2002) use similar rules to delete suspected data-entry errors.

[34] Less than 0.3% of observations are winsorized as a result. The results are qualitatively the same without winsorization.

unexpected news (or "earnings surprise") will be the absolute deviation of the announced earnings from the most recent forecasts. I use the absolute value of the forecast error of the previous quarter (APFE: $|e_{j,q-1} - F_{i,j,q-1}|$) as a proxy for the size of the unexpected news. The most recent forecast of the analyst for the quarter is used to compute the forecast error of the previous quarter.

- Earnings uncertainty ($1/\nu_0$).

  I use two proxies for ex-ante earnings uncertainty. The first one is the dispersion of forecasts before the prior quarter's earnings announcements (DISP), and the second is the idiosyncratic volatility of daily stock returns (RETVOL) estimated from the market model over the period from 90 to 3 days before the announcement.

- Initial reputation ($\bar{\nu}_1$).

  I use a performance measure based on an analyst's relative forecast accuracy during the previous year as a proxy for the initial reputation of the analyst. Following Hong, Kubik, and Solomon (2000), I rank analysts that cover a firm in a quarter based on the absolute forecast errors of their most recent forecasts for the quarter. The analyst with the smallest forecast error is given the lowest rank.[35] The rank is transformed into a score measure to adjust for the differences in the number of analysts following the firm.

[35] If two or more analysts were equally accurate, I assign all those analysts the midpoint value of the ranks they take up.

Specifically, for analyst i following firm j, the accuracy score of the analyst for the quarter q is calculated as follows.

$$score_{i,j,q} = 100 - \left[\frac{rank_{i,j,q} - 1}{n_{j,q} - 1}\right] \times 100, \tag{3.18}$$

where $rank_{i,j,q}$ is the rank of analyst i based on the absolute value of her forecast error for the quarter q of the firm j. $n_{j,q}$ is the number of analysts following firm j for quarter q. I require $n_{j,q}$ to be at least two. The higher the score, the better the performance of the analyst.

After calculating the performance score of an analyst for a firm each quarter, I average the scores over the year to calculate a firm-specific performance measure (FIRMPERF). Similarly, I average the scores across all the firms the analyst is following during the year to determine a general performance measure (GENPERF).

- The degree of reputational concerns (λ),

  If an analyst has a short forecasting record, outsiders have less information about the forecasting ability the analyst. Therefore, it is likely that less-experienced analysts care more about their reputations than do more-experienced analysts. A number of studies, including Chevalier and Ellison (1999), Hong, Kubik, and Solomon (2000), Lamont (2002), and Zitzewitz (2001), examine how career concerns vary across agents with different lengths of careers. They find evidence that the effect of current actions (*e.g.,* current performance or deviation from the consensus) on career outcomes is greater among less-experienced agents, and that less-experienced agents are more likely show career-concern driven behavior such as herding or exaggeration of private information.

I use the number of years that the analyst has been in the I/B/E/S database as of the forecasting date as a measure of the analyst's general experience (GEN-EXP) and the number or quarters for which the analyst has released a quarterly earnings forecast for a firm as a measure of the analyst's firm-specific experience (FIRMEXP).

Among 617,797 one quarter ahead earnings forecast observations with available previous forecast errors, 401,535 are revised forecasts. Requiring daily stock return volatility, dispersion in forecasts, analyst's experience and previous year's performance scores reduces the sample to 292,210 observations.

Since the implication of prior earnings on current earnings differs across firms, I estimate (3.17) at the firm level and report summary results. I require that there be at least 40 observations for each regression. It reduces the sample size to 246,167 observations (1,589 firms).

3.4.3 Results

Table A.10, Panel A provides sample descriptive statistics. Correlations among the variables are shown in Panel B.

As documented in previous studies, the mean forecast error is negative but the median forecast error is close to zero. Preliminary evidence of underreaction is found from the simple correlation coefficient between the forecast error (FE) and prior forecast error (PFE), which is positive and significant ($\rho = 0.193$, p-value$= 0.000$).

I replicate prior studies on analysts' underreaction to prior earnings news by regressing forecast error (FE) on the previous forecast error (PFE) (equation (3.16)). I estimate the regression coefficients for each firm and and report the summary of results in Table A.11. Consistent with prior studies, I find that analysts underreact to earnings information. The average regression coefficient of PFE is positive and significant $(0.244, p < 0.001)$.

I test the predictions of the model by investigating whether the degree of analysts' underreaction, measured by the regression coefficient for the prior forecast error (β_j), varies with variables of interest. I include the proxy variables and their interaction terms with the previous forecast error in the basic regression equation. Rewriting equation (3.17),

$$\begin{aligned} e_{j,q} - F_{i,j,q} &= \alpha_j(\boldsymbol{Z}_{i,j,q}) + \beta_j(\boldsymbol{Z}_{i,j,q})(e_{j,q-1} - F_{i,j,q-1}) + \varepsilon_{i,j,q} \\ \alpha_j(\boldsymbol{Z}_{i,j,q}) &= \sum_k \alpha_{jk} z^k_{i,j,q} \\ \beta_j(\boldsymbol{Z}_{i,j,q}) &= \sum_k \beta_{jk} z^k_{i,j,q} \end{aligned} \tag{3.19}$$

where the z^k's are variables that proxy for the parameters in the model (including constant). A negative coefficient of the interaction term (β_{jk}) indicates that analysts underreact less as the variable z^k increases. In the test, z^k = Constant, APFE, DISP, RETVOL, GENPERF, FIRMPERF, GENEXP, or FIRMEXP.

Table A.12 presents the results of the firm-level estimation of (3.19) using ordinary least squares. The number of observations per regression ranges from 40 (minimum required) to 1,441, with an average of 155 observations per firm. Results only for the interaction terms (β_{jk}) are reported.

Consistent with the model, there is very strong evidence that analysts underreact less as the size of unexpected earnings news (APFE) increases. In model 1, for example, the t-statistics of the regression coefficient for the size of unexpected earnings news (APFE) interacted with prior forecast error is -2.22 and Z-statistics is -13.31, all significant at 5% level.

Analysts also appear to underreact less as the uncertainty about the earnings increases, as measured by forecast dispersion and idiosyncratic stock return volatility. This is also consistent with the model's prediction. The coefficient of the forecast dispersion (DISP) when interacted with the prior forecast error is negative, which implies that analysts underreact to prior earnings news less when the dispersion of forecasts among the analysts following the firm is greater. Z-statistics are significant, while t-statistics are not. Since there are relatively few observations per regression, there are a few extreme coefficient estimates that affect the t-values. The Z-statistics, which put less weight on the less reliable coefficient estimates by scaling each coefficient estimate by its standard deviation, show more stability across different specifications. For example, I find that Z-statistics for the RETVOL interaction term is significantly negative while the mean coefficient is positive. But after eliminating extreme coefficient estimates (1% each tail; Table A.12), the mean coefficient becomes negative.

Since less-experienced analysts are likely to have greater career concerns than more-experienced analysts, the model predicts more underreaction to public news among younger analysts. Consistent with the prediction of the model and also with the results presented by Mikhail, Walther, and Willis (2001), I find that more-experienced analysts underreact less than less-experienced analysts. The regression coefficient of the past forecast error is smaller for more experienced analysts, as shown by the negative coefficient of the interaction term between the experience variable and the prior forecast error. The results are similar whether I use general experience (GENEXP) or firm-specific experience (FIRMEXP).

On the other hand, I find that analysts with better past performance underreact less. The results show that the coefficients of the interaction terms for prior performance (GENPERF, FIRMPERF) are negative. If past performance proxies for an analyst's initial reputation, then the evidence is in contrast to the prediction of the model. Unlike other comparative statics, the prediction about the effect of the initial ability $\bar{\nu}_1$ on analysts' underreaction is derived under the assumption that the dispersion in ability is constant. If the assumption does not hold, it is not clear how the initial reputation (or ability) will affect the degree of analysts' underreaction. The sign of the comparative statics with respect to ν_1^H is ambiguous, which implies that the effect of a high type analyst's ability on the degree of underreaction to public information can be positive or negative. Also, it is possible that analysts with better past forecast accuracy are those who care less about their reputations and more about forecast accuracy. If past forecast accuracy is negatively related to the degree of career concerns, the effect of the prior forecast accuracy on the extent of underreaction can go in the opposite direction.

As a robustness check, I estimate the same regressions with data starting from 1990. It has been documented (e.g., O'Brien (1988)) that the lags between the date of an analyst's forecast and its entry into I/B/E/S was up to a month in the early 1980s. After 1988, improvements in technology reduced this turn-around time to less than 24 hours (see the discussion in Kutsoati and Bernhardt (2000)). Since I examine forecasts that are reported after the prior quarter's earnings announcements, the delay can add noise to the estimates. I get qualitatively similar results (untabulated) when I exclude data from 1980s.

3.5 Conclusion

This chapter provides a theoretical and empirical analysis of analysts' incentives to incorporate public information in their earnings forecasts. While analysts' underreactions have been well documented, relatively few studies have examined the sources of their underreactions.

I develop a model of analysts' forecast revisions around public news and show that analysts may underreact to public information owing to reputational concerns. The model generates empirical predictions regarding the factors that determine analysts' incentives to underreact. I test the implications of the model by examining how the degree of analysts' underreactions to prior earnings news varies with the size of unexpected news, earnings uncertainty, and analyst characteristics. I find that analysts underreact to earnings news more when the size of the earnings surprise is small, when the earnings uncertainty is low, and when analysts have short track records, consistent with the predictions of the model. On the other hand, I find that the past forecast accuracy of the analyst is negatively related to the degree of underreaction.

The model also implies that analysts' strategic biases can lead to divergent responses in forecasts to public announcements, consistent with the empirical finding of Kandel and Pearson (1995). Furthermore, the stock market may react to revisions in analyst forecasts made in response to information that has already been incorporated into stock prices, because the revisions may convey information about the analyst's pre-existing forecasts.

CHAPTER 4

CONCLUSION

This dissertation studies how psychological and rational considerations affect individual investors and security analysts. The first essay provides evidence that the trading decisions of individual investors are partly driven by their desire to feel good about the outcome of their stock investments. The tendency of individual investors to realize multiple losses on the same day and gains over different days can be interpreted as a result of their preference for integrating losses and segregating gains. This study is closely related to recent theoretical and empirical studies that examine the role of mental accounting in asset pricing and corporate finance. The results of this study complements other studies on the trading behavior of individual investors and provides further implications about the stock market.

The second essay shows that analysts' reputational concerns can result in insufficient forecast revisions after public news. While analysts' underreaction has been well-documented, relatively few studies examine the sources of their underreaction. This essay contributes to the existing literature by examining a possible cause of analysts' underreaction and by generating new insights on when analysts have greater incentives to report forecasts that do not fully incorporate public information.

APPENDIX A

TABLES AND FIGURES

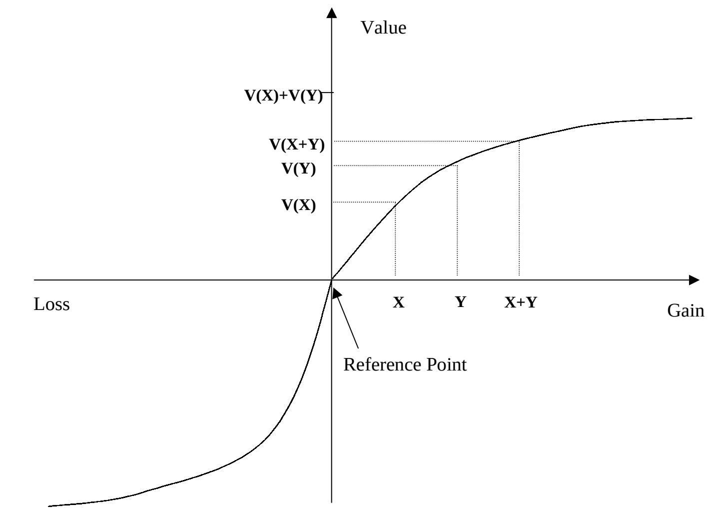

Figure A.1: Multiple Gains: Segregation Preferred

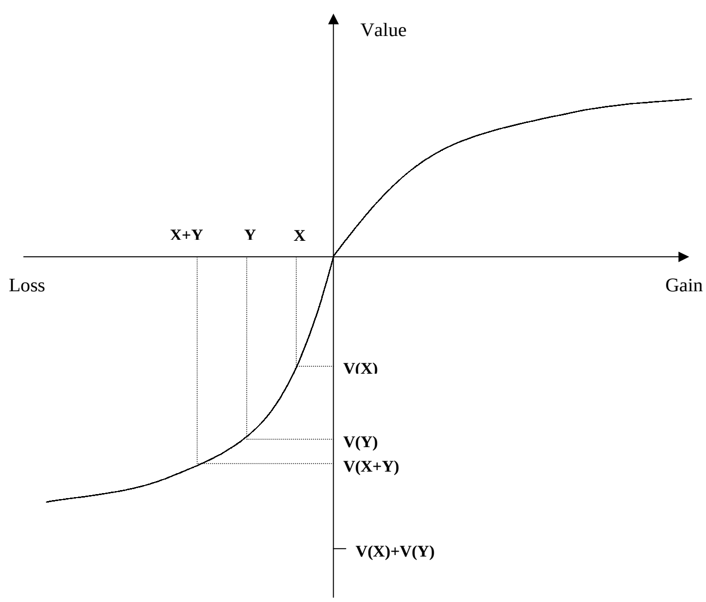

Figure A.2: Multiple Losses: Integration Preferred

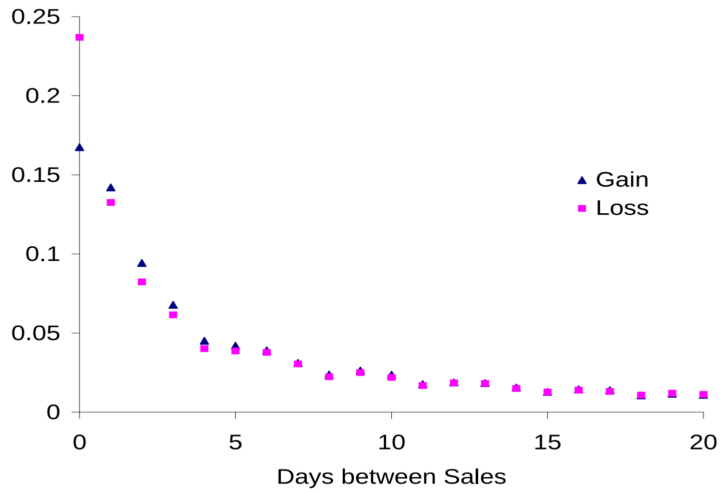

Figure A.3: Distribution of the Interval between Sales

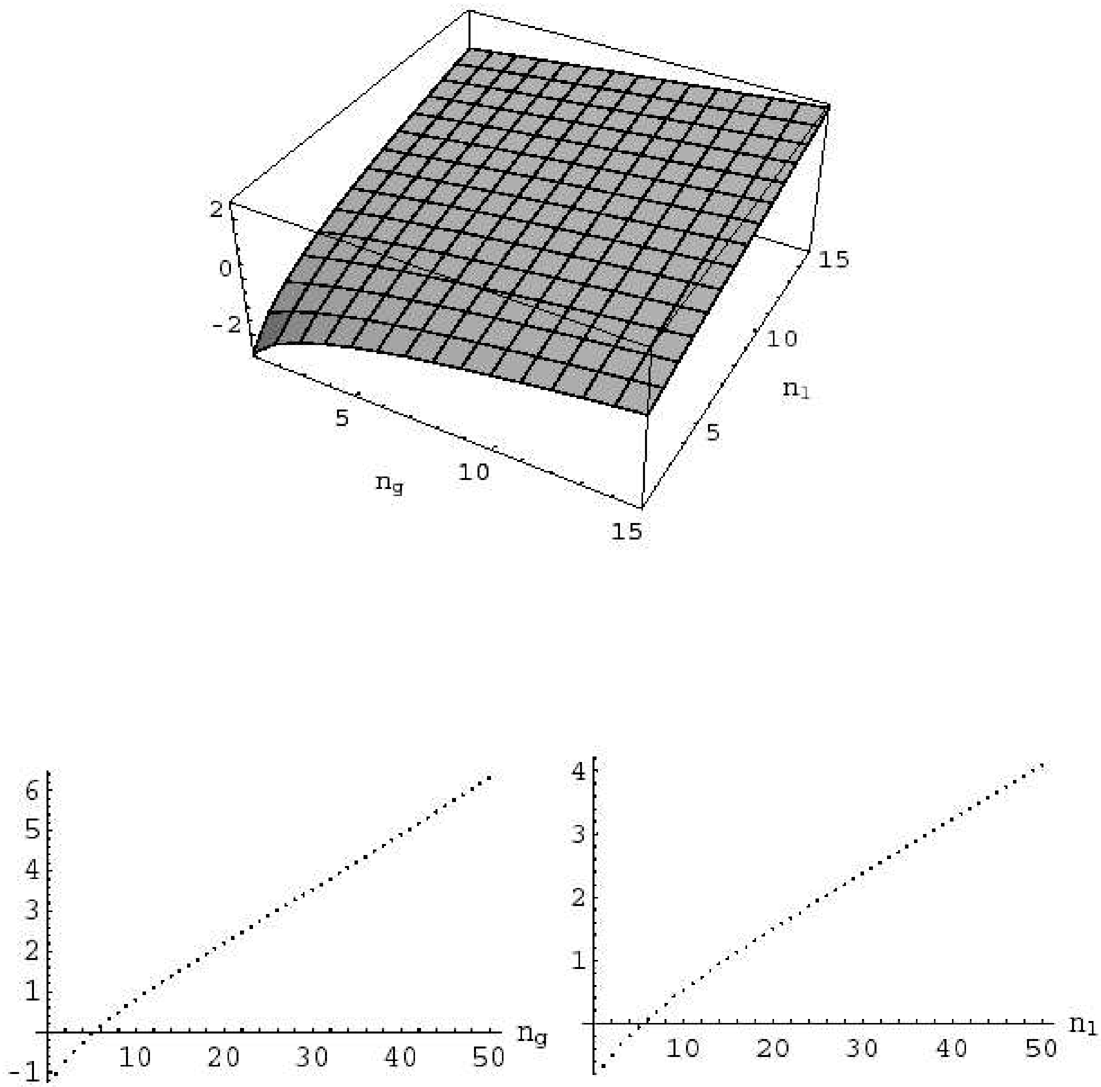

Figure A.4: Logit of Probability of Multiple Stock Sales as a Function of Number of Winners (n_g) and Losers (n_l) ($p_g = 0.148$, $p_l = 0.098$)

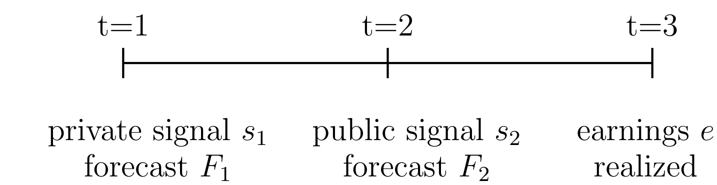

Figure A.5: Timeline of the Basic Model

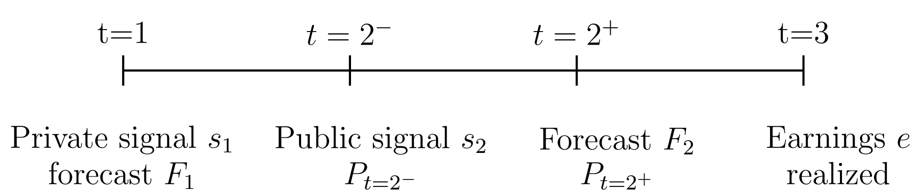

Figure A.6: Timing of the Events

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 A. Number of Accounts

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 B. Number of Sales Events

	Dollar value per stock		Capital gain/loss per stock		# of stocks	
	mean	median	mean	median	mean	median
Realized Winner Portfolio	$22,987	$8,767	$4,433	$1,238	1.15	1
Realized Loser Portfolio	$17,121	$5,425	-$3,483	-$938	1.19	1
Paper Winner Portfolio	$19,457	$7,993	$4,614	$1,202	4.84	3
Paper Loser Portfolio	$12,528	$5,388	-$2,711	-$979	4.32	3
Winner Portfolio	$20,964	$8,725	$4,620	$1,369	4.6	3
Loser Portfolio	$13,501	$5,577	-$2,875	-$1,047	3.9	2
Entire Portfolio	$17,922	$7,792	$1,130	$205	8.6	5

Panel C. Portfolio Characteristics at Sales Events

Table A.1: Sample Descriptive Statistics

Table A.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.

	# 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 A. Entire Sample

	Affluent			**General**			**Trader**		
	# of stocks sold		Multiple stock sales %	# of stocks sold		Multiple stock sales %	# of stocks sold		Multiple stock sales %
	1	≥ 2		1	≥ 2		1	≥ 2	
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%
Diff.			2.78%			2.18%			1.58%
t-stat			9.69			15.40			10.56

Panel B. By Client Segment

	Jan.-Nov.			**December**		
	# of stocks sold during the day		Multiple stock sales %	# of stocks sold during the day		Multiple stock sales %
	1	≥ 2		1	≥ 2	
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

Panel C. Jan.-Nov. vs. December

Table A.2: Proportion of Multiple Stock Sales: Gain vs. Loss

Table A.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. 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.

	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 A. Taxable vs. Retirement 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

Panel B. Margin vs. Non-Margin Accounts

Table A.3: Proportion of Multiple Stock Sales: By Account Characteristics

Table A.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. 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.

	# 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 A. Entire Sample

	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

Panel B. 1991-1994 vs. 1995-1996

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

Table A.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. 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.

	# of stocks sold 1	≥ 2	Multiple stock 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 A. Difference in dollar values between winners and losers less than 10%

	# of stocks sold 1	≥ 2	Multiple stock 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	

Panel B. When the dollar value of a loser is greater than the dollar value of a winner

Table A.5: Proportion of Multiple Stock Sales: Potential Proceeds Control

Table A.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 for a winner and a loser is less than 10% at the beginning of the sales date (Panel A) and when the dollar value of a loser is greater than the dollar value of a winner 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. 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.

		# 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 A.6: Correlations of Returns and Index of Relatedness: Winner vs. Loser

Table A.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 repective 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	Mean	t-statistics
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 A. Entire Sample

		# Obs	Mean	t-statistics
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

Panel B. Exclude December Sales

Table A.7: Difference in the Multiple Stock Sales Probabilities: An Account Level Analysis

For accounts with at least 5 sales events, I calculate the proportion of multiple stock sales for gains and for losses and the difference between them $(Pr(Multi|Loss) - Pr(Multi|Gain))$ for each account. The differences are aggregated across accounts. In Panel B, sales events in December are excluded.

Table A.8 Logistic Analysis of the Propensity to Sell Multiple Stocks

Table A.8 reports maximum likelihood estimates of regression coefficients and z-statistics for logistic regressions. On each day when a stock is sold, the dependent variable takes the value of one if the investor sells multiple stocks, and zero if he sells only a single stock. 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 they are at gains
DECEMBER	: dummy equal to 1 for December sales
MARGIN	: dummy for margin accounts
LNSTOCK	: log (number of stocks in the portfolio)
NLOSER	: number of losers in the portfolio
NWINNER	: number of winners in the portfolio
TAXABLE	: dummy for taxable accounts
TRADER	: dummy for active traders
AFFLUENT	: dummy variable for affluent households
DOLLARPOSI	: average dollar position of a stock in the portfolio (in million dollars)
PURCHASE	: dummy variable equal to 1 when the account makes purchases on the same day
NTOTSALES	: 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 the 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 (return)^2 of market over days [-60,-1]

	(1)	(2)	(3)	(4)	(5)	(6)
LOSS	0.151	0.138	0.11	0.114	0.117	0.105
	(5.60)**	(5.19)**	(4.18)**	(4.31)**	(4.45)**	(4.01)**
LOSS*DECEMBER	0.48	0.465	0.468	0.465	0.466	0.469
	(7.05)**	(7.82)**	(7.86)**	(7.74)**	(7.82)**	(7.81)**
LOSS*TAXABLE	0.031	0.038	0.043	0.044	0.044	0.044
	(1.08)	(1.34)	(1.53)	(1.56)	(1.56)	(1.55)
DECEMBER	-0.049	-0.139	-0.142	-0.113	-0.122	-0.115
	(-0.87)	(-3.72)**	(-3.77)**	(-2.91)**	(-3.21)**	(-2.97)**
LNSTOCK	0.688	0.673	0.682	0.686	0.686	0.685
	(93.97)**	(89.25)**	(90.18)**	(89.93)**	(89.71)**	(89.48)**
MARGIN	0.062	0.074	0.072	0.069	0.069	0.069
	(2.96)**	(3.54)**	(3.42)**	(3.29)**	(3.29)**	(3.27)**
TAXABLE	-0.109	-0.107	-0.107	-0.11	-0.11	-0.11
	(-4.39)**	(-4.30)**	(-4.32)**	(-4.46)**	(-4.42)**	(-4.44)**
ACTIVE	0.015	-0.003	-0.008	-0.005	-0.005	-0.005
	(1.04)	(0.19)	(0.55)	(0.35)	(0.34)	(0.35)
AFFLUENT	-0.072	-0.064	-0.054	-0.048	-0.048	-0.049
	(-3.49)**	(-3.07)**	(-2.60)**	(-2.32)*	(-2.32)*	(-2.34)**
DOLLARPOSI	-0.53	-0.654	-0.471	-0.478	-0.484	-0.481
	(-3.21)**	(-3.81)**	(-2.88)**	(-2.93)**	(-2.96)**	(-2.95)**
NTOTSALES		0.001	0.001	0.001	0.001	0.001
		(14.90)**	(15.93)**	(19.46)**	(18.81)**	(19.36)**
PURCHASE		0.301	0.299	0.299	0.298	0.297
		(20.51)**	(20.50)**	(20.51)**	(20.50)**	(20.47)**
VWHPRET			-0.141	-0.142	-0.145	-0.138
			(-7.70)**	(-8.08)**	(-7.93)**	(-7.66)**
PFRET0			-3.038			-2.751
			(-10.14)**			(-9.63)**
PFRET1			0.043		0.043	0.05
			(2.88)**		(2.42)**	(2.65)**
PFRET2_5			-0.213		-0.065	-0.12
			(-1.08)		(0.44)	(-0.74)
PFRET6_20			0.079		0.088	0.066
			(1.07)		(1.23)	(0.94)
MKTVOL				50.007	47.193	51.026
				(6.66)**	(6.21)**	(6.80)**
MKTRET0				-6.108		-2.221
				(-5.40)**		(-1.96)*
MKTRET1				-5.656	-6.773	-5.739
				(-4.73)**	(-5.59)**	(-4.79)**
MKTRET2_5				-1.773	-1.713	-1.523
				(-2.97)**	(-2.76)**	(-2.45)**
MKTRET6_20				-0.219	-0.314	-0.291
				(-0.67)	(-0.92)	(-0.86)
Pseudo-R^2	5.21%	5.91%	5.84%	5.87%	5.85%	5.74%
Observations	400417	400417	400268	400417	400268	400268

Table A.8: Logistic Analysis of the Propensity to Sell Multiple Stocks

	(1)	(2)	(3)	(4)	(5)	(6)
NLOSER	0.043	0.039	0.036	0.036	0.036	0.035
	(31.33)**	(28.24)**	(27.32)**	(28.02)**	(28.19)**	(27.66)**
NWINNER	0.029	0.023	0.025	0.026	0.025	0.026
	(21.66)**	(17.44)**	(18.33)**	(19.27)**	(19.06)**	(19.52)**
DECEMBER		0.087	0.085	0.111	0.097	0.106
		(3.53)**	(3.64)**	(5.42)**	(4.51)**	(5.18)**
MARGIN		0.064	0.064	0.064	0.064	0.063
		(3.95)**	(3.91)**	(3.92)**	(3.91)**	(3.88)**
TAXABLE		0.003	0.002	0	0.001	0
		(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)**
DOLLARPOSI		-1.001	-0.972	-0.965	-0.982	-0.973
		(-7.02)**	(-6.85)**	(-6.85)**	(-6.94)**	(-6.88)**
NTOTSALES		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	46.35	25.33	20.29	23.08	17.02
p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
Pseudo-R^2	2.79%	3.85%	4.02%	4.01%	3.98%	4.11%
Observations	425749	425749	425598	425749	425598	425598

Table A.9: Logistic Analysis of the Propensity to Sell Multiple Stocks - an Alternative Approach

Chi-square test statistics for testing equality of the coefficient for NWINNER and the coefficient for NLOSER are reported with p-values.

Variable	Mean	Median	Q1	Q3	Std.Dev
FE (x10^{-2})	-0.098	0.007	-0.132	0.128	0.994
PFE (x10^{-2})	-0.009	0.025	-0.065	0.134	0.783
APFE (x10^{-2})	0.304	0.106	0.037	0.285	0.721
DISP(x10^{-3})	0.024	0.0017	0.0003	0.0081	0.27
RETVOL (x10^{-3})	0.81	0.477	0.23	1.004	1.001
FIRMPERF	51.44	51.84	38.22	65.28	20.36
GENPERF	50.0	50.96	46.46	55.79	7.58
FIRMEXP	14.87	12	6	21	11.13
GENEXP	8.34	8	4	12	4.55

Table A.10: Sample Description

Table A.10 provides descriptive statistics for the sample of 1,589 firms for which there are at least 40 quarterly earnings forecasts (total 246,167 observations). Only revised forecasts for which the following is available are considered: the analyst's forecast for the prior quarter, dispersion of forecasts and idiosyncratic volatility of daily stock returns of the firm measured over a period [-90,-3] of the prior quarter's earnings announcement, the analyst's performance score for the previous year and the analyst's forecasting experience.

Variable Definitions

FE	error of the revised forecast for the current quarter, actual earnings minus the forecast $(e_{j,q} - F_{i,j,q})$
PFE	forecast error of the previous quarter, using the most recent forecast for the quarter $(e_{j,q-1} - F_{i,j,q-1})$
APFE	absolute value of the PFE
DISP	dispersion of forecasts before the prior quarter's earnings announcement
RETVOL	idiosyncratic volatility of daily stock returns from the market model over period a $[-90, -3]$ of the prior quarter's earnings announcement.
FIRMPERF	firm-specific performance measure calculated by averaging the accuracy score of the analyst over the previous year.
GENPERF	general performance measure calculated by averaging the accuracy score over the previous year and all the firms the analyst is following during that year.
FIRMEXP	number or quarters for which the analyst has released a quarterly earnings forecast for the firm as of the forecasting date.
GENEXP	number of years that the analyst is in the I/B/E/S database as of the forecasting date.

Variable	Average coefficient	t	Z
Intercept	-0.00125	-13.69**	-12.46**
PFE	0.244	19.14**	23.66**
Ave. Adj. Rsq	6.6%		

Table A.11: Analysts' Underreaction to Prior Earnings News: Summary of the Basic Firm-Level Regressions
** p-value < 0.05,* p-value < 0.1

z^k	model 1	model 2	model 3	model 4	model 5	model 6
APFE	-40.08 (-2.22)** [-13.31]**	-39.82 (-2.29)** [-12.76]**	-42.09 (-2.46)** [-13.09]**	-40.97 (-3.03)** [-13.36]**	-46.35 (-3.85)** [-13.30]**	-42.33 (-3.59)** [-13.53]**
DISP (x10^3)	-4,218 (-0.93) [-3.75]**	-2,765 (-0.87) [-3.95]**	-2,963 (-0.88) [-3.51]**			
RETVOL				-1.616 (-0.02) [-2.09]**	19.65 (0.24) [-1.95]*	11.94 (0.15) [-2.02]**
GENEXP		-0.0074 (-2.85)** [-2.27]**	-0.0049 (-1.9)* [-2.71]**		-0.005 (-1.76)* [-1.95]*	-0.0046 (-1.6) [-3.29]**
FIRMEXP	-0.0054 (-1.92)* [-2.80]**			-0.0063 (-2.05)** [-3.2]**		
GENPERF			-0.003 (-1.1) [-2.3]**			
FIRMPERF	-0.0009 (-1.78)* [-1.7]*	-0.0011 (-2.38)** [-1.66]*		-0.001 (-1.52) [-2.19]**	-0.0012 (-2.12)** [-2.52]**	
Average Adj. Rsq	23.3%	22.9%	22.9%	21.0%	20.4%	20.4%

Table A.12: The Effects of Event and Analyst Characteristics on the Analysts' Underreaction to Prior Earnings News: Summary of the Firm-Level Regressions

T-statistics are in the parenthesis and Z-statistics that do not assume unit variance are presented in brackets. **p-value < 0.05,* p-value < 0.1.

z^k	model 1	model 2	model 3	model 4	model 5	model 6
APFE	-42.34 (-8.56)** [-13.69]**	-42.17 (-8.32)** [-13.06]**	-43.82 (-8.81)** [-13.37]**	-34.52 (-7.15)** [-13.55]**	-36.74 (-7.15)** [-13.45]**	-35.46 (-7.03)** [-13.63]**
DISP ($x10^3$)	-7.382 (-0.76) [-3.76]**	-10.204 (-1.05) [-4.00]**	-5.752 (-0.59) [-3.44]**			
RETVOL				-53.68 (-1.07) [-2.64]**	-27.46 (-0.55) [-2.62]**	-44.33 (-0.89) [-2.56]**
GENEXP		-0.0056 (-3.10)** [-2.34]**	-0.0048 (-2.59)** [-2.99]**		-0.003 (-1.46) [-2.04]**	-0.0043 (-2.32)** [-3.58]**
FIRMEXP	-0.101 (-2.34)** [-2.88]**			-0.004 (-2.65)** [-3.28]**		
GENPERF			-0.0021 (-2.1)** [-2.56]**			
FIRMPERF	-0.0006 (-2.00)** [-1.61]	-0.0005 (-1.73)* [-1.60]		-0.0004 (-1.24) [-2.42]**	-0.002 (-2.3)** [-2.48]**	
Average Adj. Rsq	23.3%	22.9%	22.9%	21.0%	20.4%	20.4%

Table A.13: The Effects of Event and Analyst Characteristics on the Analysts' Under-reaction to Prior Earnings News: Summary of the Firm-Level Regressions, Excluding Extreme Coefficient Estimates (1% each tail)

T-statistics are in the parenthesis and Z-statistics that do not assume unit variance are presented in brackets. **p-value < 0.05,* p-value < 0.1.

APPENDIX B

PROOFS AND A NUMERICAL EXAMPLE

Proof of Proposition 1.

1. A separating equilibrium where each type reports the conditional expectation e truthfully.

For (3.9) to be an equilibrium, a low type analyst should (weakly) prefer issuing a forecast truthfully than mimicking a high type.

$$
\begin{aligned}
& - \quad E\left[\left\{e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2}\right)(s_2 - F_1)\right\}^2\right] + \lambda \nu_1^H \\
& \leq \quad -E\left[\left\{e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}\right)(s_2 - F_1)\right\}^2\right] + \lambda \nu_1^L
\end{aligned} \tag{B.1}
$$

$$
|s_2 - F_1| \geq \frac{\sqrt{\lambda}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)}{\nu_2 \sqrt{\nu_1^H - \nu_1^L}} \tag{B.2}
$$

When $|s_2 - F_1|$ is sufficiently large or λ is small, a low ability analyst will issue the true conditional expectation $F_2^L = E^L[e|s_1, s_2]$.

2. A separating equilibrium where the high type reports a forecast that does not fully incorporate the public signal to separate from the low type.

When $|s_2 - F_1| < \sqrt{\lambda}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)/\nu_2 \sqrt{\nu_1^H - \nu_1^L}$, a separating equilibrium where both types issue forecasts truthfully does not exist because a low type will deviate and mimic a high type. Suppose that the high ability analyst biases her forecast as follows.

$$F_2^H = F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} - b \right) (s_2 - F_1) \tag{B.3}$$

where $b > 0$.

The high type chooses the smallest b that prevents the low type from mimicking. Thus, b should satisfy the following conditions.

For the high type,

$$\begin{aligned} & - E\left[\left\{ e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} \right) (s_2 - F_1) \right\}^2 \right] + \lambda \nu_1^H \\ & > -E\left[\left\{ e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} \right) (s_2 - F_1) \right\}^2 \right] + \lambda \nu_1^L \end{aligned} \tag{B.4}$$

and for the low type,

$$\begin{aligned} & - E\left[\left\{ e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} \right) (s_2 - F_1) \right\}^2 \right] + \lambda \nu_1^H \\ & \leq -E\left[\left\{ e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2} \right) (s_2 - F_1) \right\}^2 \right] + \lambda \nu_1^L. \end{aligned} \tag{B.5}$$

From (B) and (B.5),

$$\frac{\sqrt{\lambda(\nu_1^H - \nu_1^L)}}{|s_2 - F_1|} + \frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} - \frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2} \leq b < \frac{\sqrt{\lambda(\nu_1^H - \nu_1^L)}}{|s_2 - F_1|} \tag{B.6}$$

The smallest b that satisfies the conditions (B) and (B.5) is

$$b = \frac{\sqrt{\lambda(\nu_1^H - \nu_1^L)}}{|s_2 - F_1|} + \frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} - \frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}. \tag{B.7}$$

Thus, the high-type analyst will report the date-2 forecast of the following form.

$$\begin{aligned} F_2^H &= F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2} - b\right)(s_2 - F_1) \\ &= F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2} - \frac{\sqrt{\lambda(\nu_1^H - \nu_1^L)}}{|s_2 - F_1|}\right)(s_2 - F_1) \\ &= F_1 + \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}\right)(s_2 - F_1) - \sqrt{\lambda(\nu_1^H - \nu_1^L)}\frac{(s_2 - F_1)}{|s_2 - F_1|} \end{aligned} \tag{B.8}$$

From the equation (B.8), the bias b is such that the cost of a biased forecast just offsets the reputational gain $\lambda(\nu_1^H - \nu_1^L)$ for the low type from mimicking the high type.

3. A pooling equilibrium.

Suppose outsiders believe that both high and low ability analysts update as specified in equation (3.11). A high ability analyst will issue the conditional expectation of e, $F_2^H = F_1 + \nu_2(s_2 - F_1)/(\nu_0 + \nu_1^H + \nu_2)$ since it minimizes the mean squared error and the analyst will be perceived as a low type if he deviates from it.

A low type analyst will mimic the high type and issue a biased forecast than an unbiased one if doing so results in a higher value of the objective function.

$$
\begin{aligned}
& - \quad E\left[\left\{e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^H + \nu_2}\right)(s_2 - F_1)\right\}^2\right] + \lambda[\mu\nu_1^H + (1-\mu)\nu_1^L] \\
& \geq \quad -E\left[\left\{e - F_1 - \left(\frac{\nu_2}{\nu_0 + \nu_1^L + \nu_2}\right)(s_2 - F_1))^2\right\}\right] + \lambda\nu_1^L
\end{aligned}
\tag{B.9}
$$

After arranging terms, it becomes

$$
|s_2 - F_1| \leq \frac{\sqrt{\lambda\mu}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)}{\nu_2\sqrt{\nu_1^H - \nu_1^L}}
\tag{B.10}
$$

$\|$

Proof of Corollary 1.

The range of s_2 where underreaction occurs is derived from the incentive conditions of a low type analyst.

Given F_1, s_2 is distributed normally with mean F_1 and variance $(\nu_0+\nu_1^L+\nu_2)/(\nu_2(\nu_0+\nu_1^L))$ for the low type. Then, the probability of condition (3.12) being satisfied given F_1 is

$$
\begin{aligned}
& Pr\left[|s_2 - F_1| \leq \frac{\sqrt{\lambda}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)}{\nu_2\sqrt{\nu_1^H - \nu_1^L}} \mid F_1\right] \\
= \quad & Pr\left[|z| \leq \frac{\sqrt{\lambda}(\nu_0 + \nu_1^H + \nu_2)(\nu_0 + \nu_1^L + \nu_2)}{\nu_2\sqrt{\nu_1^H - \nu_1^L}}\sqrt{\frac{\nu_2(\nu_0 + \nu_1^L)}{\nu_0 + \nu_1^L + \nu_2}} \mid F_1\right] \\
= \quad & Pr\left[|z| \leq (\nu_0 + \nu_1^H + \nu_2)\sqrt{\frac{\lambda(\nu_0 + \nu_1^L + \nu_2)(\nu_0 + \nu_1^L)}{\nu_2(\nu_1^H - \nu_1^L)}} \mid F_1\right],
\end{aligned}
\tag{B.11}
$$

where z is a standard normal random variable with mean 0 and variance 1. Since the above probability does not depend on the value of F_1, the unconditional probability is the same. As we can see, the probability of underreaction occurring is increasing with ν_0 and λ.

Let us define d as the difference of the date-1 signal precision of a high type and of a low type analyst.

$$d = \nu_1^H - \nu_1^L \tag{B.12}$$

ν_1^H and ν_1^L can be written in terms of $\bar{\nu}_1$ and d,

$$\begin{aligned} \nu_1^H &= \bar{\nu}_1 + (1-\mu)d \\ \nu_1^L &= \bar{\nu}_1 - \mu d \end{aligned} \tag{B.13}$$

$$Pr\left[|z| \leq (\nu_0 + \bar{\nu}_1 + (1-\mu)d + \nu_2)\sqrt{\frac{\lambda(\nu_0 + \bar{\nu}_1 - \mu d + \nu_2)(\nu_0 + \bar{\nu}_1 - \mu d)}{\nu_2 d}}\right]. \tag{B.14}$$

If d is constant, the above probability increases with $\bar{\nu}_1$.

Therefore, the likelihood of underreaction increases with ν_0 and λ, and also with $\bar{\nu}_1$ if $d = \nu_1^H - \nu_1^L$ is constant.

$\|$

A Numerical Example of Strategic Date-1 Forecasts

Let us assume that e takes one of three possible values.

$$e = \begin{cases} -1 & , \quad Pr = 1/4 \\ 0 & , \quad Pr = 1/2 \\ +1 & , \quad Pr = 1/4 \end{cases}$$

At date-1, an analyst receives a private signal $s_1 \in (-1, 0, 1)$ about e. The analyst can be either a high or a low type ($\Theta \in (H, L)$) with equal probabilities. A high ability analyst receives more informative private signal than a low ability analyst. The conditional probabilities of signals are given below.

$Pr^H(s_1\|e)$	$s_1 = -1$	0	1
$e = -1$	4/5	1/5	0
0	1/5	3/5	1/5
1	0	1/5	4/5

$Pr^L(s_1\|e)$	$s_1 = -1$	0	1
$e = -1$	1/2	1/2	0
0	1/3	1/3	1/3
1	0	1/2	1/2

Based on the date-1 private signal, an analyst updates his/her belief about the earnings. The analyst's posterior belief about the earnings $Pr^{\Theta}(e|s_1)$ can be calculated from the prior probability $Pr(e)$ and the probability distribution of the date-1 signal conditional on e, $Pr^{\Theta}(s_1|e)$.

$Pr^H(e\|s_1)$	$s_1 = -1$	0	1
$e = -1$	2/3	1/8	0
0	1/3	3/4	1/3
1	0	1/8	2/3

$Pr^L(e\|s_1)$	$s_1 = -1$	0	1
$e = -1$	3/7	3/10	0
0	4/7	2/5	4/7
1	0	3/10	3/7

The analyst issues the date-1 forecast F_1 that maximizes the following objective function.

$$\max_{F_1 \in \{-1,0,1\}} U_1(F_1|s_1) \equiv -E[(e - F_1)^2|s_1] + \lambda Pr^O(\Theta = H|F_1), \tag{B.15}$$

where $Pr^O(\Theta = H|F_1)$ is the posterior belief of outsiders about the type of the analyst given the analyst's date-1 forecast F_1. Note that the objective function of the analyst is myopic since it does not take into account outsiders' further inferences about the analyst's ability at date-2.

It can be easily shown that a forecast that minimizes the mean squared error $E[(e - F_1)^2|s_1]$ in this example is e with the highest posterior probability $Pr^\Theta(e|s_1)$. From the posterior probabilities calculated above, a low type analyst minimizes the mean squared error by reporting $F_1 = 0$ regardless of the private signal and a high type analyst follows one's private signal.

Suppose that the analyst reports F_1 that minimizes the mean squared error in an equilibrium. Then outsiders conclude that the analyst is a high-type when they observe $F_1 = 1$ or -1. If the reputational concern of the analyst is sufficiently large (specifically, $\lambda > 1/7$), a low type analyst will deviate and issue a forecast that differs from zero.

For $\lambda \in (497/60, 3497/60)$, there is an equilibrium at date-1 where the low type mimics the high type by issuing a forecast that is same as one's private signal.

$$F_1^H = F_1^L = s_1.$$

As a consequence, a low type analyst acts as if the weight on one's private signal is greater than it actually is (exaggeration).

At date-2, the analyst receives a public signal s_2. Conditional on the earnings, s_1 and s_2 are independent. Assume that the analyst's date-2 objective function is similar to the date-1 objective function.

$$\max_{F_2 \in \{-1,0,1\}} -E[(e-F_2)^2 | s_1, s_2] + \lambda Pr^O(\Theta = H | F_1, F_2) \tag{B.16}$$

The probability distribution of the date-2 signal is as follows.

$Pr(s_2\|e)$	$s_2 = -1$	0	1
$e = -1$	3/5	2/5	0
0	1/4	1/2	1/4
1	0	2/5	3/5

Note that the public signal is not as informative as the private signal of the high type, but it is more informative than the low type's private signal. Thus, for certain values of the public signal, a high type analyst will not revise the forecast (e with the highest posterior probability will be the same) while a low type analyst needs to revise the forecast whenever the public signal differs from one's private signal.

$Pr^H(s_1, s_2\|e)$	$(s_1, s_2) =$ $(-1,-1)$	(-1,0)	(-1,1)	(0, -1)	(0,0)	(0, 1)	(1, -1)	(1,0)	(1,1)
$e = -1$	12/25	8/25	0	3/25	2/25	0	0	0	0
0	1/20	1/10	1/20	3/20	3/10	3/20	1/20	1/10	1/20
1	0	0	0	0	2/25	3/25	0	8/25	12/25

$Pr^L(s_1, s_2\|e)$	$(s_1, s_2) =$ $(-1,-1)$	(-1,0)	(-1,1)	(0, -1)	(0,0)	(0, 1)	(1, -1)	(1,0)	(1,1)
$e=-1$	3/10	1/5	0	3/10	1/5	0	0	0	0
0	1/12	1/6	1/12	1/12	1/6	1/12	1/12	1/6	1/12
1	0	0	0	0	1/5	3/10	0	1/5	3/10

The posterior probabilities $Pr^\Theta(e|s_1, s_2)$ are:

$Pr^H(e\|s_1, s_2)$	$(s_1, s_2) =$ $(-1,-1)$	(-1,0)	(-1,1)	(0, -1)	(0,0)	(0, 1)	(1, -1)	(1,0)	(1,1)
$e=-1$	24/29	8/13	0	2/7	2/19	0	0	0	0
0	5/29	5/13	1	15/21	15/19	15/21	1	5/13	5/29
1	0	0	0	0	2/19	2/7	0	8/13	24/29

$Pr^L(e\|s_1, s_2)$	$(s_1, s_2) =$ $(-1,-1)$	(-1,0)	(-1,1)	(0, -1)	(0,0)	(0, 1)	(1, -1)	(1,0)	(1,1)
$e=-1$	9/14	3/8	0	9/14	3/11	0	0	0	0
0	5/14	5/8	1	5/14	5/11	5/14	1	5/8	5/14
1	0	0	0	0	3/11	9/14	0	3/8	9/14

As we can see from the date-2 posterior probabilities, forecast revisions after public news may indicate that the analyst is a low type. For example, when $(s_1, s_2) = (0, 1)$, a low type analyst should revise the forecast from $F_1 = 0$ to $F_2 = 1$. However, doing so reveals that the analyst is of a low type because $F_2 = 0$ for a high type analyst. Therefore, a low type analyst may not revise one's forecast after the public signal, which results in underreaction to public news. This numerical example shows that analysts may underreact to public news at date-2 even when they report their date-1 forecasts strategically.

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