THREE ESSAYS ON

STOCK RECOMMENDATIONS

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ABSTRACT OF THE DISSERTATION

Three Essays on Stock Recommendations

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This dissertation studies stock recommendations made by columnists and financial analysts. The first essay examines the value and profitability of columnist recommendations published in the Business Week, Forbes and Fortune magazines. Empirical results show that columnist recommendations are not profitable in the short- or long-run controlling for market risk, book-to-market, size and momentum effects. The second essay examines the relation between the value of analysts' recommendations and corporate research and development (R&D) investments. Univariate, calendar-time portfolio and cross-sectional analyses controlling for risk, business complexity, earnings value-relevance, analyst coverage, institutional ownership and bid-ask spread indicate the value of analysts' recommendations to be significantly more valuable for firms that are more intensely engaged in R&D investments. The final essay, using stock recommendations, examines Regulation FD's impact on corporate practice of earnings-related selective disclosure to financial analysts. The comparative analysis of the association between analysts' revisions and subsequent earnings surprises, in the pre- and post- Regulation FD periods reveals a significant reduction in analysts' earnings-related private information in the post-Regulation FD period.

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Dedication

To my parents and sister.

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Chapter 1 The Value of Columnists' Stock Recommendations

1.1 Introduction

Business magazines remain well and alive amid today's high-tech and fast serving information intermediaries such as websites and data feeds. Business magazines continue to cater to readers interested in keeping up with financial markets and to those who are in the process of making investment decisions. Leading business magazines are still read by millions and advertisement spots in these publications are highly demanded. For the six-month period ending in June 31st, 2005, Business Week, Forbes and Fortune magazines each reported readership figures in ranges of three to five million readers - exceeding 13 million readers combined (see Table 1.1).

Despite their reach to wide investor masses, research on columnists' stock recommendations is overshadowed by research on financial analysts. The literature often regards financial analysts as investors' sole source of advice and sets aside other sources as either similar to analysts or minor in follower size. Nevertheless, columnists are highly influential in investors' decisions and differ from financial analysts in many respects.

This essay examines a large sample of columnist recommendations published in business magazines. Previous research on this area is concentrated only on a few columns and is limited to the short term market reaction to columnists' recommendations. Whether the documented findings are similar for columnists in other magazines is an unanswered empirical question. Further, there is no prior research on what types of stocks columnists recommend, the content of columnist recommendations and what columnist recommendations' long-term performance is.

This essay extends research on columnists on several fronts. First it employs an extensive sample encompassing all stock recommendations made by leading business magazines. This gives more room to generalize empirical results to the columnist profession. Further, the essay examines how recommendations' timing, content and style are associated with recommendations' market reaction. Finally, the long-term performance of columnists' stock recommendations is examined.

The empirical results suggest that previous studies' findings on columnists are not pervasive in the large sample of columnist recommendations this essay examines. Published results on certain columnists are actually limited to those specific columnists and documented findings are not a profession wide phenomenon. These results reaffirm Fama's (1998) concerns of only anomalous findings being published in the literature.

Further, the findings indicate that recommendations with references to management officials or containing merger and acquisition news generate significantly greater market reactions. Overall, the results expand the understanding of columnist recommendations' impact on prices, the long-term value of recommendations to investors and the relation between recommendations' qualitative characteristics and their market impact.

The remainder of this paper is organized as follows. Section 2 provides an overview of the literature. Section 3 describes the data and explains the methodology. Section 4 presents and discusses the empirical results, and section 5 concludes.

1.2 Literature Review

Researchers have focused on market reaction to columnists' stock recommendations for several decades. In fact research on columnist recommendations dates back to Cowles's

(1933) early study. Cowles, in his study, examined Wall Street Journal editor William Peter Hamilton's recommendations and found them to be inferior to a buy and hold strategy. Since then, numerous studies have investigated the return behavior surrounding columnists' stock recommendations.

Particularly after Fama, Fisher, Jensen, and Roll's (1969) event study on dividend announcements and Fama's (1970) efficient markets hypothesis there was an increase in research studying stock recommendations. In this period, Lloyd-Davies and Canes (1978) (hereafter, LC) examined the performance of second-hand information published in the Wall Street Journal (Heard on the Street) for the period, 1970 – 1971. They documented that Wall Street Journal (WSJ) articles affected stock prices on publication day. This implied that columnists could have traded and generated abnormal profits based on the column's information prior to its publication. More interestingly the columns did not provide any information that was not available to the public, they merely repeated previous news. LC argued that the publication effect on returns suggested that not all publicly available information was fully reflected in prices and WSJ articles helped markets adjust to previously disseminated information. Lloyd-Davies and Canes' findings, although for a limited sample, provided evidence against strong-form efficient market hypothesis. Later Liu, Smith and Syed (1990) and Beneish (1991) found confirming results using data from 1982 – 1985 and 1978 – 1979, respectively. Palmon, Sun and Tang (1994) also documented similar behavior for stocks mentioned in the "Inside Wall Street" column of Business Week magazine for the period 1983 – 1989. However, different from LC, later studies also documented reversals in prices to pre-publication levels. In most studies, a slow reversal was spotted within the 20 – 25 day period following recommendations. In addition, Liu et al. and Palmon et al. documented a significant increase in trading volume during the three days centered on the publication day of the columns. On the other hand Lee (1986) measured the abnormal returns before and after the publication of the Forbes column written by Heinz H. Biel. He found that recommendations did not allow investors to consistently outperform the market but provided useful information.

The aforementioned studies relied on the information hypothesis to explain recommended stocks' return behavior surrounding the publication day. The information hypothesis claimed that columns' publication revealed new information to the public and this yielded an abnormal return on publication day.

A stream of subsequent articles relied on the price pressure hypothesis to explain abnormal returns on the publication day. The price pressure hypothesis asserted that heavy buying pressure by naïve investors drove abnormal returns on publication day.

Sant and Zaman (1996) and Mathur and Waheed (1995) were among the studies that relied on the price pressure hypothesis. These studies examined price reactions to stocks mentioned in Business Week's "Inside Wall Street" column for the periods; 1976 – 1988 and 1981 – 1989, respectively. Barber and Loeffler (1993), Metcalf and Malkiel (1994), and Liang (1999) examined Wall Street Journal's Dartboard column for a period covering the early 1990s. Pari (1987) and Ferreira and Smith (2003) looked at recommendations brought up in the television program Wall $treet Week. These studies, using the price pressure hypothesis brought an explanation to the positive abnormal returns on the publication day and negative returns during the subsequent 20 days.

The literature provides evidence on specific columns in the financial press. Prior results suggest that columnist recommendations have an economically significant impact on firm market value. However, whether these results can be generalized remains unclear. In addition, prior research only studies the implications of recommendations' final output (e.g. buy or sell) on asset prices. There are no prior studies examining the relation between market reaction and recommendations' timing, content and style. This essay aims to fill this gap in the literature by studying a large sample of columnist recommendations, examining the relation between recommendations' market impact and contextual characteristics and assessing recommendations' long-term performance.

1.3 Data and Methodology

1.3.1 Data

Information on all stock recommendations made in the three leading business magazines; Business Week, Forbes and Fortune during the four-year period between 2000 and 2003 were hand collected. These magazines were selected on the basis of their wide circulation and readership (see Table 1.1). The following information was recorded into a database for each stock recommendation:

- columnist name,
- recommended trading position,
- columnist's source of information (whether it relied on his research or someone else's research),

- recommendation content (e.g. contained a reference to other investors, managers or analysts, whether the recommendation had merger and acquisition or product related news)
- date on the cover of the issue.

The final sample, which is the intersection of CRSP (Center for Research in Security Prices) and the recommendation sample excluding ambiguous recommendations, consists of 2503 buy recommendations.[1] Dates on the cover of magazines do not indicate magazines' publication dates. To identify the first day that readers had access to magazines, magazine sale dates for each magazine was retrieved from the Standard Rate and Data Service – Consumer Magazine volumes.

Data on return, price, shares outstanding and trading volume were obtained from the CRSP's daily file, quarterly earnings announcement dates from Compustat's quarterly file and accounting data from Compustat's annual file. Financial analysts' consensus recommendation ratings were computed using the I/B/E/S recommendation file and earnings forecasts were derived from the I/B/E/S's detail file. In addition, all upgrades made by financial analysts were obtained from the I/B/E/S recommendation file.

Data on bid-ask spreads were collected from the TAQ database and the Gibbs and Amihud liquidity variables were included from the database made available by Joel Hasbrouck. Finally, Fama and French (1993) and Carhart (1997) factor returns and Fama & French industry classifications were downloaded from Kenneth French's website.[2]

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[1] In addition to buy recommendations there were 129 sell recommendations in the sample. Due to the limited number of observations, sell recommendations were excluded from the analysis.

[2] I thank Kenneth French and Joel Hasbrouck for making their data available.

1.3.2 Event Study Methodology: A Review

Event-study analysis has been widely applied to investigate research questions in numerous academic fields including accounting, economics, finance and law (see Binder (1998)). The event-study methodology allows researchers to measure the economic impact of an event on firm value and test market efficiency. One of the earliest studies to use the event study methodology was Dolley (1933) who investigated the impact of stock-splits on security prices. Myers and Bakay (1948), Barker (1956) and Ashley (1962) were other early studies that used the event study analysis. The seminal studies by Ball and Brown (1968) and Fama, Fisher, Jensen and Roll (1969) developed the event study methodology substantially and a variation of their methodology continues to be in use today.

Since event study analysis's development, a wide range of methodologies has been applied to estimate the economic impact associated with events and corporate developments. These include (1) mean adjusted returns model, (2) market adjusted returns model, (3) market and risk adjusted returns model, (4) calendar-time portfolio approach, (5) Ibbotson's returns across time and securities (RATS) approach, (6) event parameters approach and (7) cross-sectional stochastic dominance approach.

The mean adjusted returns model estimates abnormal returns (e_{it}) as the difference between raw returns (R_{it}) and a firm-specific constant expected return (C_i): $e_{it} = R_{it} - C_i$. The market adjusted returns model assumes expected returns for all firms to be equal to the market return and estimates abnormal returns as the difference between raw and market returns: $e_{it} = R_{it} - R_{mt}$. The market and risk adjusted returns model estimates abnormal returns based on expected returns derived from an asset pricing model (e.g.

CAPM, three-factor, four-factor model). This method involves a two-stage estimation whereby first risk sensitivities are estimated and in the second stage these sensitivities are used to compute expected ($E[R_{it}]$) and abnormal (e_{it}) returns: $e_{it} = R_{it} - E[R_{it}]$. In the calendar-time portfolio approach a rolling portfolio is formed each period which includes all sample firms remaining in the event period. When CAPM is assumed to be the asset pricing model, constructed portfolio's excess returns are regressed on excess market returns and the intercept (also known as the Jensen's alpha) of the regression is used as an estimate of abnormal returns. Ibbotson's RATS approach developed by Ibbotson (1975) computes abnormal returns as the intercept of the cross-sectional regression that is estimated for each event period. This approach is particularly useful in estimating abnormal returns when there is no historical return data to estimate market model parameters. The event parameters approach developed by Binder (1985) and Schipper and Thompson (1983) relies on the simultaneous estimation of a system of equations which conditions the return generating process on the occurrence of an event. To accomplish this, the market model (or multifactor model) is augmented with a dummy variable that equals one if an event took place and zero otherwise. The event parameter approach possesses the advantage of providing test statistics that potentially reflect the cross-sectional covariance among firms. Finally, the cross-sectional stochastic dominance approach examines the whole distribution of returns of assets and tests whether investors can increase expected utility by investing in an alternative asset. The primary advantage of this approach is that it does not make distributional assumptions and does not require the identification of risk measures. There are three major types of stochastic dominance: first-order, second-order and third-order. The first-order stochastic dominance makes no assumption regarding investors' risk preference, the second-order assumes that investors are not risk preferring and the third-order assumes decreasing absolute risk aversion. Larsen and Resnick (1999) based on simulations find that the stochastic dominance approach augmented with the bootstrap method performs as well and at times better than traditional event study methodologies.

In this study, to analyze the short-term behavior surrounding recommendations I use the market and risk-adjusted returns model and to assess the long-term performance of recommendations I use the calendar-time portfolio regression approach which was also used by Jaffe (1974) and Mandelker (1974) and advocated by Mitchell and Stafford (2000).

1.3.2.1 Short-Term Return Analysis

This essay uses the four-factor model to measure the short term market reaction to columnists' recommendations. The four-factor model relies on the linear relationship between returns of individual stocks, market, size, book-to-market and momentum portfolios. For any security *i*:

$$\mathrm{R}_{\mathrm{it}} = \alpha_i + \beta_i \mathrm{R}_{\mathrm{mt}} + s_i \mathrm{SMB}_{\mathrm{t}} + h_i \mathrm{HML}_{\mathrm{t}} + u_i \mathrm{UMD}_{\mathrm{t}} + \xi_{it} \qquad (1)$$

where R_{it} is firm i's return on day t, R_{mt} is the CRSP value weighted index return for day t, SMB is the average return on the three small portfolios (value, neutral and growth) minus the average return on the three big portfolios (value, neutral and growth), HML is the average return on the two value portfolios (small and big) minus the average return on the two growth portfolios (small and big), UMD is the average return on the two high prior return portfolios (small and big) minus the average return on the two low prior return portfolios (small and big).[3] ε_{it}, is a zero-mean disturbance term. The parameters of equation (1) are estimated using a 255 day estimation period (between $\tau - 46$ and $\tau - 300$ where τ is the event date).

The abnormal return for the ith asset on day t is defined as:

$$\mathrm{AR}_{\mathrm{it}} = \mathrm{R}_{\mathrm{it}} - (\hat{\alpha}_i + \hat{\beta}_i \mathrm{R}_{\mathrm{mt}} + \hat{s}_i \mathrm{SMB}_{\mathrm{t}} + \hat{h}_i \mathrm{HML}_{\mathrm{t}} + \hat{u}_i \mathrm{UMD}_{\mathrm{t}})$$

where the coefficients $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{s}_i$, $\hat{h}_i$ and $\hat{u}_i$ are ordinary least squares estimates of α_i, β_i, s_i, h_i, and u_i in equation (1).

The cumulative average abnormal return for the period between T_1 and T_2 is:

$$\mathrm{CAAR}_{\mathrm{T_1,T_2}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \sum_{\mathrm{t=T_1}}^{\mathrm{T_2}} \mathrm{AR}_{\mathrm{it}}.$$

The null hypothesis of $\mathrm{CAAR}_{\mathrm{T_1,T_2}} = 0$ is tested using the following test statistic:

$$\mathrm{t} = \frac{\mathrm{CAAR}_{\mathrm{T_1,T_2}}}{\hat{\sigma}_{\mathrm{AAR}} \sqrt{\mathrm{T_2 - T_1 + 1}}} \sim \mathrm{N}(0,\ 1)$$

where $\hat{\sigma}^2_{\mathrm{AAR}} = \dfrac{\sum_{\mathrm{t=T_1}}^{\mathrm{T_2}} (\mathrm{AAR_t} - \overline{\mathrm{AAR}})^2}{\mathrm{T_2 - T_1 - 1}}$ and $\overline{\mathrm{AAR}} = \dfrac{\sum_{\mathrm{t=T_1}}^{\mathrm{T_2}} \mathrm{AAR_t}}{\mathrm{T_2 - T_1 - 1}}$.

The generalized sign z test-statistic, a non-parametric test-statistic, is also reported. Cowan (1996) based on simulations using daily stock return data finds the generalized sign test to be well specified and superior to the rank test when investigated

[3] Fama and French (1993) construct the six portfolios used in the calculation of SMB and HML factor returns at the end of each June using the intersections of two portfolios (small and big) formed on size (market equity) and three portfolios (value, neutral and growth) formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in t-1 divided by ME for December of t-1. The BE/ME breakpoints are the 30th and 70th NYSE percentiles.

securities have thin trading, large return variance or the examined event windows are long. To compute the generalized sign test statistics the ratio of positive abnormal returns during the estimation period (255 days) are measured:

$$\hat{p} = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{255}\sum_{t=E_1}^{E_{255}} S_{jt}$$

where

$$S_{jt} = \begin{cases} 1 & \text{if } AR_{jt} > 0 \\ 0 & \text{otherwise} \end{cases}.$$

Then using the positive to negative abnormal return ratio from the estimation period as the expected ratio for the test window I calculate the number of positive abnormal returns (w) and measure its divergence from the expectation as $Z = \dfrac{w - n\hat{p}}{(n\hat{p}(1-\hat{p}))^{1/2}}$.

1.3.2.2 Abnormal Trading Volume Analysis

To measure abnormal trading volume behavior I use the market model approach described in Ajinkya and Jain (1989) and Campbell and Wasley (1996).[4] In this methodology a trading volume metric for each day and security is computed and regressed on CRSP equally weighted index's trading volume metric. The residuals derived from this estimation are then used as the abnormal trading volume indicator.

The trading volume metric is computed as follows:

$$V_{it} = \log\left[\frac{n_{it} \times 100}{S_{it}} + 0.000255\right] \qquad \textbf{(2)}$$

[4]The methodology to estimate abnormal trading volume is consistent with Barber and Loeffler (1993) and Liang (1999).

where n_{it} is the number of shares traded for firm i on day t, S_{it} is the firm's outstanding number of shares on day t. As suggested by the results in Ajinkaya et al. and Cready and Ramanan (1991), I use the log-transformation of percentage of shares traded. Before taking the log-transformation, a small constant of 0.000255 is added to prevent taking the log of zero, in case there is no trading volume on any firm day (as in Campbell et al.).

The market model abnormal trading volume is as follows:

$$\mathrm{V}_{\mathrm{it}} = \gamma_i + \rho_i \mathrm{V}_{\mathrm{mt}} + v_{it}. \tag{3}$$

And abnormal trading volume is defined as:

$$v_{it} = \mathrm{V}_{\mathrm{it}} - (\hat{\gamma}_i + \hat{\rho}_i \mathrm{V}_{\mathrm{mt}})$$

where $\hat{\gamma}_i$ and $\hat{\rho}_i$ are ordinary least squares estimates of the trading volume market model parameters. V_{mt} is computed as the sum of the trading volume metric of all securities in the CRSP equally weighted index:

$$\mathrm{V}_{\mathrm{mt}} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{V}_{\mathrm{it}} .$$

1.3.2.3 Regression Analysis

In addition to the univariate analysis, a regression analysis of publication returns is conducted to examine the variation in returns to recommendations' source, timing and content while controlling for liquidity, information leakage, information asymmetry and size factors. Using ordinary least squares (OLS) the following equation is estimated:

$$\begin{aligned} \mathrm{CAR}(-1,+1)_{\mathrm{i}} = \alpha &+ \beta_1 \mathrm{IWS}_{\mathrm{i}} + \beta_2 \mathrm{SPREAD}_{\mathrm{i}} + \beta_3 \mathrm{CAR}(-10,-2)_{\mathrm{i}} + \beta_4 \mathrm{FOR\_STD}_{\mathrm{i}} + \beta_5 \mathrm{RND}_{\mathrm{i}} \\ &+ \beta_6 \mathrm{SIZE}_{\mathrm{i}} + \beta_7 \mathrm{DIRECT}_{\mathrm{i}} + \beta_8 \mathrm{REF\_ANLYST}_{\mathrm{i}} + \beta_9 \mathrm{REF\_MGMT}_{\mathrm{i}} \\ &+ \beta_{10} \mathrm{MERGER\_NEWS}_{\mathrm{i}} + \beta_{11} \mathrm{PRODUCT\_NEWS}_{\mathrm{i}} + \beta_{12} \mathrm{CNFDG} \\ &+ \textstyle\sum_{k=1}^{49} \phi_k \mathrm{IND} + \varepsilon_{\mathrm{i}}. \end{aligned} \tag{4}$$

where the dependent variable CAR(-1, +1) is the three-day cumulative abnormal return centered on the date of recommendation, IWS is an indicator variable that takes a value of one (zero otherwise) for recommendations published in the Inside Wall Street column, SPREAD is the trade-weighted relative bid-ask spread computed based on all transactions made during the most recent calendar-month before the recommendation date is used to control for liquidity, CAR (-10,-2) is the cumulative abnormal return during the 9-day period ending two days before the recommendation, FOR_STD is the standard deviation of analysts' earnings forecasts and RND_INTENSITY is the ratio of R&D expenditure and sales for the most recent fiscal year assuming a reporting lag of three-months and SIZE is the natural logarithm of the recommended firm's market value.[5] [6]

To examine the relation between recommendations' contextual characteristics and their market reactions several indicator variables are included in the regression analysis. DIRECT is an indicator variable that takes a value of one for recommendations that rely on the columnist's own analysis rather than other sources' (e.g. analysts, money managers) analysis. REF_ANLYST, REF_INV, and REF_MGMT are indicator variables that take a value of one for recommendations that make references to analysts, investors, and management, respectively. MERGER_NEWS and PRODUCT_NEWS are indicator variables that take a value of one for recommendations that contain merger & acquisition

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[5] When R&D expenditure is missing I replace it with zero.

[6] Another potential factor that can be used to control for information asymmetry is the number of analyst following. However, this variable is highly correlated with firm size. In untabulated analysis I exclude firm size from the regression model, control for analyst following and find similar results.

rumor and product news, respectively. CNFDG is an indicator variable that takes a value of one for recommendations that follow an earnings announcement, analysts forecast, recommendation or other columnist's recommendations within a seven-day period. Finally, the regression model contains Fama and French 49 industry fixed-effects, IND, to control for industry effects.

1.3.2.4 Long Term Performance Analysis

To measure the long term abnormal performance of stock recommendations a rolling value-weighted daily portfolio that takes positions in shares of recommended firms is constructed. A recommended stock enters the portfolio one day after the magazine's publication date and remains in the portfolio for one year. The portfolios value-weighted daily return is computed as

$$VW_{pd} = \frac{\sum_{m=1}^{n_{p,t}} R_{m,d} \times mv_{m,d-1}}{\sum_{m=1}^{n_{p,d}} mv_{m,d-1}}$$

where $R_{m,d}$ is the day d return on security m, $n_{p,d}$ is the number of firms in the portfolio and $mv_{m,d-1}$ is the market value of firm m on day d-1. The daily portfolio returns are compounded to monthly returns, R_{pt}, as follows:

$$R_{pt} = \left[\prod_{t=1}^{n_d} (1 + R_{pd}) \right] - 1$$

where n_d is the number of trading days in the month t and R_{pd} is the raw monthly return for the portfolio on day d. Then, using OLS, this portfolio's monthly excess returns are regressed on excess market returns, size, book-to-market and momentum factor returns.[7]

$$R_{pt} - R_{ft} = \alpha + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + h_i HML_t + u_i UMD_t + \xi_{it} \qquad (5)$$

where R_{pt} is the value-weighted monthly return for month t, R_{ft} is the Ibbotson One Month Treasury Bill Rate. The market and factor returns are as defined in equation (1). In this regression, the intercept (also known as the Jensen's alpha) is an estimate of the average monthly abnormal return accumulated by holding the portfolio during the estimation period.

1.4 Empirical Results

1.4.1 Short-Term Return Behavior

The short-term return analysis reveals that share prices of firms recommended by columnists increase prior to and on publication day. The running cumulative average return for columnist recommendations, illustrated in Figure 1.1, begins increasing three to four days prior to publication day and rises sharply on publication day. The cumulative average abnormal return for the three day period centered on the publication day is 1.41 percent (Table 1.2 Panel A) which is statistically significant at the one-percent significance level.

However, the increase in prices prior to and on publication day of columnist recommendations is temporary. Part of the cumulative return accumulated up to

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[7] Excess return is raw monthly return minus the one-month Treasury Bill rate (monthly).

publication day is reversed within the twenty-day period following columnist recommendations. In comparison to the 1.41 percent market reaction on publication the cumulative average abnormal return for the (+2, +20) is -1.60 percent which is statistically significant at the one-percent significance level.

Analyst upgrades are also associated with a strong market reaction leading up to announcement date which however is not followed by a price reversal. The cumulative average abnormal return for the three-day period centered on analyst upgrades' publication day is 3.02 percent (Table 1.2 Panel B). The 3.02 percent market reaction is statistically significant based on both parametric and non-parametric tests. In contrast to columnist recommendations, analyst upgrades do not exhibit a price reversal during the post-event period. The cumulative average abnormal return for analysts' upgrades for the (+2, +20) event window is -0.02 percent and the median CAR is 0.29 percent. In untabulated analysis, the mean difference between the cumulative average abnormal return (+2, +20) of analysts' and columnists' recommendations is found to be statistically significant.

The return behavior following analyst and columnist recommendations is substantially different. The results indicate no price reversal for analyst upgrades whereas a strong price reversal follows columnists' stock recommendations. The evident price reversal for columnist recommendations is consistent with the price pressure hypothesis whereby no new information is released to the markets but prices temporarily increase because of buying pressure imposed by investors. On the other hand, financial analysts' upgrades appear to reveal more information which the markets incorporate into prices without a subsequent short-term price reversal.

The return behavior documented for columnists is substantially weaker in magnitude than findings of prior studies that examine particular columns in business magazines. For instance, Palmon, Sun and Tang (1994), Mathur and Waheed (1995), and Sant and Zaman (1996) find that the cumulative average abnormal return for publication ranges between 2.44% and 3.25% whereas this study documents a 1.41 percent market reaction on publication.

A potential explanation for the difference between this essay's findings and prior studies' results is the used sample. Prior studies focus on particular columns whereas this study examines a large sample of columnist recommendations from several leading business magazines.

The most widely examined business magazine column in the prior literature is the Inside Wall Street (IWS) column of Business Week magazine. In search of an explanation for differences between my findings and prior findings I split the sample into four sub-samples: IWS, Business Week (excluding IWS), Forbes and Fortune.

The sub-sample analysis reveals that the Inside Wall Street column drives the full sample results. The return behavior surrounding IWS recommendations is substantially different from other sub-sample results. The publication cumulative average abnormal return for IWS recommendations is 4.61 percent (Table 1.2 Panel C) which is more than three times greater than the average market reaction for the full-sample. Table 1.2 Panels D-F report that the market reaction to recommendations published in Business Week's other columns, Forbes and Fortune magazines are 0.3, 0.55, and 0.65 percent, respectively. Although average market reactions to non-IWS recommendations are also statistically significant they are considerably weaker than the reaction to IWS recommendations. In untabulated analysis I test and find the difference in market reactions between IWS and Business Week, Forbes and Fortune to be statistically significant.

As in the full-sample results, IWS recommendations are also followed by a price reversal. The cumulative average abnormal return for the post-publication event window (+2, +20) is -3.45 percent which is statistically significant. Interestingly a similar negative return behavior follows Business Week's columns other than IWS. However I do not find a statistically significant price reversal for Forbes and Fortune magazines' recommendations.

Further, the trading volume reaction to IWS recommendations is strongest within the entire sample including analyst upgrades. Figure 1.2 illustrates the trading volume reaction for recommendations published in the IWS column, Business Week, Forbes and Fortune magazines and financial analysts' upgrades. The mean abnormal relative volume for IWS recommendations on publication day is 160 percent whereas analyst upgrades' mean abnormal relative volume is 90 percent. Most strikingly, the mean trading volume reaction to IWS recommendations is approximately 20 times greater than the mean volume reaction to recommendations published in Business week, Forbes and Fortune.

In addition to the striking abnormal return and trading volume behavior associated with recommendations published in the Inside Wall Street column there is a long history of scandals linked to the IWS column dating back to 1988. Table 1.3 provides a sample of news reports related to the Inside Wall Street column. The incidences linked to the IWS column show investors' strong ambition to obtain access to IWS columns prior to publication and act on the recommendations therein. Investors' effort to act based on IWS recommendations partly explains the observed abnormal return and trading volume behavior.

However, the underlying reason why IWS attracts strong investor interest while other columns receive little interest from investors remains unclear. In search of an explanation as to why IWS recommendations are associated with a different return and trading volume behavior I examine whether differences in recommended firms' financial characteristics or recommendations' content, style, and timing play a role.

The empirical analysis of recommended firms' financial characteristics – reported in Table 1.4– reveals that firms recommended in the Inside Wall Street column are smaller than firms recommended in other columns. Table 1.4 Panel A reports that the average firm recommended by IWS has a market value of $9.6 billion, whereas the average firm recommended by Business Week's other columns, Forbes and Fortune columns have market values of $29, $24.1 and $33.8 billion, respectively.

Investors receive information about large firms from various sources (e.g. analysts, media) whereas the number of sources for investors to acquire information on small firms is limited. The scarcity of information for small firms may put forward columnist recommendations for these firms and play a role in the strikingly different return behavior that IWS recommendations are associated with. On the other hand, firms recommended in IWS are similar to firms recommended in other columns in terms of turnover, leverage, current, price-to-book, price-to-earnings and price-to-cash-flow ratios.

Another difference between IWS and other sources may be the way recommendations are written in the IWS column. To examine potential difference in recommendations I explore the content and style of IWS recommendations in comparison to other columnist recommendations. In this analysis I examine various aspects of recommendations' style and content. For each columnist (or magazine) I compute the ratio of recommendations that:

- are direct (implying that the author relies directly and solely on his analysis),
- have references to financial analysts,
- have references to investors,
- have references to management officials,
- contain merger and acquisition related rumors,
- contain information about new product releases.

I find a substantial difference between IWS and non-IWS recommendations in terms of content and style. First of all, none of IWS recommendations are direct recommendations. Columnists publishing in IWS appear to avoid relying solely on their own analysis. They prefer supporting their recommendations with references to investors, analysts and management more often than other columnists. Table 1.4 Panel B reports that 58.8% of all IWS recommendations make references to financial analysts whereas Business Week's other columns, Forbes and Fortune columnists refer to analysts in the range of 6.3-42.86 percent. Similarly, IWS columnists in 44.1 and 6.9 percent of their recommendations make references to investors and management. Both percentages are highest among a large sample of columnists. Finally, Table 1.4 Panel B reports that IWS columnists in 27.2 and 25.2 percent of their recommendations supplement their recommendations with merger & acquisition rumors and product news. Again both of these ratios are the highest in the sample. The contextual differences between IWS and non-IWS recommendations highlight the story that columnists transmit as a potentially important factor influencing markets' response to recommendations.

In addition to recommendations' content and style, I examine recommendations timing with respect to confounding announcements. I define an announcement as confounding if it occurs seven-days prior to the columnist's recommendation. As potential confounding announcements, I consider other columnists recommendations, earnings announcements, analysts' earning forecasts and analysts' recommendation revisions.

Table 1.4 Panel C reports the percentage of recommendations with confounding announcements. The results indicate that IWS recommendations coincide with smaller number of confounding announcements. With the exception of earnings announcements, IWS recommendations rarely fall close to other columnists' recommendations, analysts' earnings forecasts and recommendations. Further, the average firm recommended by IWS has the lowest analyst following.

In summary, the univariate analysis reveals a market reaction to columnist recommendations which is both statistically and economically significant. However, the magnitude of the market reaction to columnist recommendations is not uniform across various columns within the full-sample. IWS recommendations which received the greatest prior academic interest drive the full-sample results. When IWS recommendations are excluded, the market reaction to columnist recommendations is muted in magnitude but remains statistically significant. This suggests that prior evidence on particular columnist recommendations cannot be generalized to all columnist recommendations and that the average columnist recommendation has a relatively small impact on prices compared to analysts.

1.4.2 Regression Analysis of Publication Returns

The regression analysis confirms that recommendations published in the Inside Wall Street column trigger significantly greater publication returns than other columns.
Table 1.5 model I reports the estimation results of the regression of publication returns on the IWS indicator variable and liquidity, information asymmetry, size and industry control factors.[8] In model I the IWS coefficient, estimated to be 0.024 (significant at the one-percent level), indicates that recommendations published in IWS yield an average market reaction that is 2.4 percent higher than non-IWS recommendations. This is consistent with the univariate results and suggests that the market reaction to IWS recommendations is different from other columnist recommendations.

In model I, the SPREAD coefficient is positive and SIZE is negative, consistent with small and illiquid firms being associated with stronger market reactions on publication of recommendations. However, there is no significant relation between information asymmetry (FOR_STD and RND) and publication returns. This may be because the SIZE variable subsumes most of the information asymmetry effect. Finally, the OLS results do not suggest that information leakage significantly affects publication returns of recommendations.

[8] I checked for multicolinearity by examining variance inflation factors and found no evidence in support of the presence of serious multicolinearity in any of the models. The mean & maximum variance inflation factors were 1.07 & 1.19 (model I), 1.65 & 3.55 (model II), 1.61 & 3.59 (model III) and 1.58 & 3.59 (model IV).

In model II, four indicator variables (DIRECT, REF_ANLYST, REF_INV, and REF_MGMT) are included to capture recommendations' qualitative aspects. With the exception of REF_MGMT, none of the estimated coefficients are statistically significant. The REF_MGMT coefficient is estimated to be 0.03 which indicates that recommendations that refer to communications with management officials trigger a market reaction that is on average 3 percent higher than recommendations that do not contain references to management. Finally, the IWS coefficient in model II, 0.022, is both statistically and economically significant. The significantly positive IWS coefficient is consistent with IWS recommendations being associated with a stronger average market reaction controlling also for recommendation content and style.

Estimation results of model III, which additionally include MERGER_NEWS and PRODUCT_NEWS, show that recommendations containing merger & acquisition rumor are associated with a stronger market reaction whereas the presence of product news does not appear to significantly influence market reaction. Table 1.5 Model III reports MERGER_NEWS's estimated coefficient to be 0.021 which is statistically significant and suggests that recommendation containing M&A rumor generate 2.1 percent higher abnormal returns than other recommendations. However, the PRODUCT_NEWS is estimated to have an insignificant coefficient consistent with markets not reacting differently to recommendations containing product news. Finally, the IWS coefficient in model III is estimated to be 0.019 which is statistically significant.

Regression model IV examines whether recommendation timing matters by including the indicator variable, CNFDG, which takes a value of one for recommendations that follow an earnings announcement, analysts forecast, recommendation or other columnist recommendation within a seven-day period. There is weak evidence in support of columnist recommendations close to other confounding events having a lower market reaction. However, the IWS coefficient remains robust to the inclusion of CNFDG.

The regression analysis suggests that IWS recommendations, controlling for liquidity, information asymmetry, size, and recommendations' contextual, stylistic and timing characteristics, trigger an average market reaction that is between 1.9 and 2.4 percent higher than other columns' recommendations. The difference between IWS and non-IWS recommendations is both economically and statistically significant. These results are consistent with IWS recommendations being distinct from other columnists. Hence, prior studies' results on particular columns do not appear descriptive of the return behavior surrounding columnist recommendations in general. Finally, there is evidence in support of recommendations with references to management officials or merger & acquisition rumors having 3.1 and 2.1 percent higher average market reactions.

1.4.3 Long-Term Performance Analysis of Columnist Recommendations

The calendar-time portfolio regression results show that a long-term investor (with a one-year holding period) following columnist recommendations during the years 2000-2003 would not have achieved abnormal returns after controlling for market risk, book-to-market, size and momentum effects. Table 1.6 Panel A reveals that investors acting based on columnist recommendations published in Business Week, Forbes and Fortune magazines with a one-day trading delay would have incurred a monthly average loss of 0.31 percent. Similarly, long-term investors following analyst upgrades with a one-day trading delay would have incurred a monthly average loss of 0.15 percent. Finally, portfolios formed according to recommendations in any of the sub-samples, IWS, Business Week excluding IWS, Forbes or Fortune do not provide significantly positive abnormal returns.

The long-term performance results are insensitive to trading delay. Even a long-term investors acting on the day of columnist recommendations would not have achieved abnormal returns controlling for beta, size, book-to-market and momentum factor sensitivities. Results reported in Table 1.6 Panel B are based on the assumption that investors are able to capture publication day returns of recommendations. According to Table 1.6 Panel B, the monthly average abnormal return associated with investing in columnist recommendations is -0.29 percent. The sub-sample analysis shows that IWS, Business Week excluding IWS, Forbes and Fortune recommendations accrue a monthly average abnormal return of 0.02, 0.21, 0.01 and -0.5 percent. However, investors able to invest in analyst upgrades on announcement day would have achieved a monthly average abnormal return of 1.2 percent based on recommendations made during 2000 – 2003.

Finally, I test for differences in long-term abnormal returns of direct and indirect stock recommendations. Direct recommendations represent stocks endorsed explicitly by columnists based on their own opinion or analysis. On the other hand, indirect recommendations generally represent endorsement by the columnists to the recommendations of others (e.g., analysts).

Columnists' choice of relying solely on analyst recommendations as opposed to their own research suggests the use of a different source of information. Indirect recommendations can be interpreted as more reliant on the efforts of analysts rather than columnists. Analysts and columnists differ in many aspects, and this has the potential to influence the abnormal returns that follow indirect and direct recommendations asymmetrically. Columnists are employed by business magazines, whereas analysts work for investment firms and brokerage houses. This gives columnists more room for independence which is documented by Barber, Lehavy and Trueman (2007) to be associated with higher performance. Columnists' greater independence provides them an environment in which they can make unbiased recommendations. Further, columnists and analysts have different incentives. Hong and Kubik (2003) discuss analysts' career concerns and find that analysts reap higher rewards when they make more optimistic recommendations. The absence of such conflicting incentives for columnists may permit them to make less biased and superior recommendations. On the other hand, the performance of columnists is evaluated less frequently. This can reduce columnists' incentives for in-depth research and analysis. Finally, columnists' access to supportive resources (e.g., data, information, research) is often more limited.

Panel A of Table 1.7 reports summary statistics of directly and indirectly recommended firms' size, previous-year-return, turnover ratio and average short-term returns preceding recommendations. The results suggest that columnists' direct recommendations are mainly composed of larger stocks with lower preceding returns and turnover ratios. Further, stocks that are recommended directly have lower abnormal returns in the period preceding the recommendation. The higher average abnormal return that precedes indirect recommendations is consistent with greater information leakage taking place prior to indirect recommendations. Indirect recommendations are more likely to involve prior dissemination to the public. Hence, positive prior returns may be due to the release of information in the pre-recommendation period. Panel B of Table 1.7

reports that direct recommendations' market risk and size factor sensitivities are significantly lower than indirect recommendations' sensitivities. These results combined, suggest that columnists – when making direct recommendations – avoid stocks that are risky, small and that have recently increased in value.

Separate portfolios constructed according to indirect and direct recommendations do not significantly outperform the market controlling for market risk, size, book-to-market and momentum effects. Table 1.8 Panel A reports the percentage monthly abnormal returns of portfolios formed with a one-day trading delay. The results suggest that neither indirect nor direct recommendations have significant long-term value to investors. These results are robust to forming portfolios without any trading delay. Table 1.8 Panel B reports estimation results for portfolios constructed without a trading delay. As in Panel A neither portfolio is significantly associated with significant abnormal returns. These results suggest that both direct and indirect recommendations fail to outperform the market controlling for market risk, size, book-to-market and momentum effects.

1.5 Conclusion

This essay investigates the abnormal return and trading volume behavior surrounding columnists' stock recommendations. For a subset of the sample, limited to recommendations published in the Inside Wall Street (IWS) column, the results are similar to prior studies' findings. However the return behavior associated with IWS is not pervasive within the full sample which includes columnists' recommendations from several leading business magazines. These results indicate that prior studies' findings are not representative of the columnist community in general.

Further, the regression analysis of publication returns suggests that recommendations that make references to management officials, or contain merger and acquisition news trigger a larger market reaction. Consistent with the prior literature, recommendations targeting illiquid and small firms coincide with a stronger market reaction.

Finally, long-term investors following recommendations published in Business Week, Forbes and Fortune magazines during the period 2000-2003 would not have been able to consistently earn abnormal returns controlling for market risk, size, book-to-market and momentum effects.

This essay's empirical analysis is subject to several limitations. First, only columnist recommendation published during the 2000-2003 period were examined. This period primarily corresponds to a bear market. Further, several major scandals (e.g. Enron, Worldcom, Parmalat) surfaced during this period. The contemporaneous market wide developments may bias the empirical results. Finally, the sample primarily consists of buy recommendations. Columnist recommendations may be diluted to the extent that columnists hide their sell recommendations and reveal their buy recommendations. Hence, the true mispricing that columnists detect can be considerably different from the results based solely on buy recommendations.

The short- and long- term return behavior surrounding columnist recommendations can also be examined using alternative methodologies. This essay relied on the use of a particular set of methods that make strict assumptions about investors' risk preferences, risk identification, and reference market portfolio. Future research relaxing these assumptions through the use of stochastic dominance approach or alternative methodologies can provide further insights about the market reaction to recommendations and the long-term value of columnists' advice.

1.6 Tables for Chapter 1

Table 1.1 Circulation and Readership Data
The circulation data for the six months ending June 31, 2005 (from the Audit Bureau of Circulation) and the readership data (from Spring 2005 MRI) are reported for the three business magazines.

Publication Name	Paid Circulation	Readers Per Copy
Business Week	985,029	4.83
Forbes	925,959	5.19
Fortune	857,309	4.26

Table 1.2 Short Term Performance of Stock Recommendations
The table below reports the abnormal returns associated with buy recommendations in the six sub-samples. Panels A-F report the abnormal returns of buy recommendations made by (A) BW, Forbes and Fortune (all columnists), (B) financial analysts, (C) Inside Wall Street, (D) Business Week excluding Inside Wall Street, (E) Forbes, and (F) Fortune. In each panel, cumulative average abnormal return (CAAR), median cumulative abnormal return (CAR), ratio of positive and negative abnormal returns, t-statistics, generalized sign test statistics and number of observations are reported for the five event windows. The symbols, *, **, *** indicate significance at five-percent, one-percent and one-tenth-percent significance levels, respectively.

Panel A: All Columnist Recommendations

	(-20, -2)	(-5, -2)	(-1, +1)	(+2, +5)	(+2, +20)
CAAR	-0.02%	0.37%	1.41%	-0.07%	-1.60%
Median CAR	0.19%	0.23%	0.61%	0.04%	-0.92%
Positive:Negative	1270:1233	1309:1194	1433:1070	1262:1240	1168:1334
t-statistics	-0.054	2.545*	11.270***	-0.516	-5.073***
Generalized Sign Test	2.442*	4.002***	8.962***	2.142*	-1.619
N	2,503	2,503	2,503	2,503	2,503

Panel B: Financial Analyst Upgrades

	(-20, -2)	(-5, -2)	(-1, +1)	(+2, +5)	(+2, +20)
CAAR	-1.45%	-0.36%	3.02%	0.18%	-0.02%
Median CAR	-1.35%	-0.23%	1.89%	0.11%	0.29%
Positive:Negative	10300:12633	10992:11941	14916:8017	11728:11201	11729:11200
t-statistics	-8.720***	-4.679***	45.705***	2.417*	-0.100
Generalized Sign Test	-11.702***	-2.560*	49.279***	7.189***	7.203***
N	22,933	22,933	22,933	22,929	22,929

Panel C: Recommendations by the Inside Wall Street Column

	(-20, -2)	(-5, -2)	(-1, +1)	(+2, +5)	(+2, +20)
CAAR	2.30%	1.34%	4.61%	-0.31%	-3.45%
Median CAR	1.57%	0.61%	2.48%	-0.13%	-1.67%
Positive:Negative	305:246	304:247	363:188	269:282	243:308
t-statistics	2.508*	3.179**	12.666***	-0.730	-3.762***
Generalized Sign Test	3.719***	3.634***	8.667***	0.648	-1.571
N	551	551	551	551	551

Panel D: Recommendations by Business Week Magazine (excluding IWS)					
	(-20, -2)	(-5, -2)	(-1, +1)	(+2, +5)	(+2, +20)
CAAR	-0.46%	-0.17%	0.30%	-0.10%	-3.89%
Median CAR	-0.24%	0.07%	0.42%	-0.15%	-3.18%
Positive:Negative	278:287	285:280	316:249	271:293	225:339
t-statistics	-0.571	-0.459	0.958	-0.274	-4.865***
Generalized Sign Test	0.379	0.968	3.578***	-0.170	-4.046***
N	565	565	565	565	565

Panel E: Recommendations by Forbes Magazine					
	(-20, -2)	(-5, -2)	(-1, +1)	(+2, +5)	(+2, +20)
CAAR	-0.99%	0.47%	0.55%	-0.07%	0.56%
Median CAR	-0.24%	0.21%	0.33%	0.25%	0.57%
Positive:Negative	387:404	411:380	432:359	417:374	415:376
t-statistics	-2.060*	2.117*	2.853**	-0.319	1.151
Generalized Sign Test	0.054	1.761	3.255**	2.188*	2.045*
N	791	791	791	791	791

Panel F: Recommendations by Fortune Magazine					
	(-20, -2)	(-5, -2)	(-1, +1)	(+2, +5)	(+2, +20)
CAAR	-0.44%	-0.15%	0.65%	0.16%	-0.58%
Median CAR	0.06%	0.14%	0.36%	0.12%	-0.62%
Positive:Negative	300:296	309:287	322:274	305:291	285:311
t-statistics	-0.634	-0.477	2.325*	0.496	-0.832
Generalized Sign Test	1.001	1.738	2.804**	1.410	-0.229
N	596	596	596	596	596

Table 1.3 “Inside Wall Street” Column Related News
Each row lists a separate news item where the first column is the date of the news; the second column indicates the source and the last column reports a representative part of the news from its full text. All news items were obtained from the Factiva database.

Date	Source	News
November 23rd, 2005	Dow Jones Newswires	*A former postal worker agreed to pay more than $580,000 to settle SEC charges that he made about $154,000 in illicit profits by trading on information from Business Week before it was delivered to subscribers.*
June 4th, 2004	Reuters News	*A stock broker accused of trading improperly on advance tips about the contents of a Business Week magazine column has been barred from the brokerage industry*
November 19th, 2003	The Capital Times & Wisconsin State Journal	*Four former Jefferson County factory workers were sentenced Tuesday in U.S. District Court in Brooklyn, N.Y., for trading on information they learned by reading the "Inside Wall Street" column in Business Week magazine printed at the Perry Judd's plant before the magazine was available to the public.*
October 17th, 2002	SEC News Digest	*Two Long Island brokers settled SEC charges that they paid cash to another broker in exchange for nonpublic, advance copies of the magazine that were obtained from a foreman at a magazine distribution facility in New Jersey.*
July 21st, 2001	Deseret News	*The insider trading conviction of a former Prudential Securities Inc. broker who was tipped off in advance about companies mentioned in Business Week's "Inside Wall Street" column has been upheld by a federal appeals court.*
February 8th, 1999	Business Week	*The heavy trading Business Week observed in the magazine's ``Inside Wall Street'' column has resulted in criminal charges against four stockbrokers. The Feds allege that the brokers bought more than $6 million in stock mentioned in Inside Wall Street on days before publication by getting copies of the column faxed from Hudson News, which distributes the magazine.*
26 January 1996	The Dallas Morning News	*Business Week has alerted regulators to a possible case of insider trading after noticing a pattern of unusual activity in stocks mentioned in its "Inside Wall Street" column. The magazine disclosed the possibility that someone may be getting an early look at its pages.*
June 6th, 1991	The Associated Press	*Two California men have settled charges that they traded on inside information obtained from advance copies of Business Week magazine, the Securities and Exchange Commission said Thursday.*
April 15th,1991	The Associated Press	*A businessman who pleaded guilty to buying stocks he knew would be mentioned in a Business Week column was sentenced Monday to three years probation and ordered to pay a $25,000 fine.*
November 9th, 1990	The Wall Street Journal	*A businessman from Wethersfield Conn., and a lawyer from Old Saybrook, Conn., was indicted by a federal grand jury in New Haven on charges of conspiracy, securities fraud, and mail fraud. They are accused of misappropriating information from Business Week's "Inside Wall Street" column prior to publication.*
May 17th, 1990	The New York Times	*The Government said that Mr. Jackson reviewed a freshly printed copy of Business Week each Wednesday night, then phoned Mr. Callahan the next morning to buy stocks recommended in the magazine's "Inside Wall Street" column.*
December 1st, 1989	Houston Chronicle	*The Business Week insider trading scandal resurfaced Thursday with civil charges brought against a typesetting supervisor who based stock trades on information contained in advance copies of the magazine.*
July 12th, 1989	The Washington Post	*A former Merrill Lynch stockbroker, his mother and three others were accused today by the Securities and Exchange Commission of purloining stock tips from advance copies of Business Week magazine in a $3.46 million insider trading case.*
December 9th, 1988	The Washington Post	*Business Week's former broadcast editor, Seymour G. "Rudy" Ruderman, pleaded guilty today to mail fraud in an insider trading scheme, admitting that he illegally used advance material from the magazine to buy and sell securities.*
August 2nd,1988	The Globe and Mail	*In addition, three more investment firms acknowledged that they are investigating trading activity involving the columns prior to their publication. That raised the number of firms involved to at least seven*

Table 1.4 Descriptive Statistics

This table provides descriptive statistics on recommended firms' financial characteristics (Panel A), recommendations' style and content (Panel B), and recommendations' timing (Panel C). Panel A reports market value (in millions), turnover, leverage, current, price-to-book, price-to-earnings and price-to-cash flow ratio averages for recommended firms (first line), industry averages (second line) and the *p*-values of the mean difference test (third line) between firm and industry averages. All variables in Panel A are winsorized at the top and bottom one percentile. Panel B reports the ratio of recommendations that are direct, the percentages of recommendations that have references to financial analysts, investors, management officials and the percentage of recommendations that contain merger & acquisition rumor and product news. Panel C reports the percentage of confounding announcements by source, analyst following and analysts' consensus recommendation rating.

Panel A: Financial Characteristics

Source	Market Value	Turnover Ratio	Leverage Ratio	Current Ratio	Price to Book Ratio	Price to Earning Ratio	Price to Cash Flow Ratio	Obs.
Inside Wall Street	9,615.2	2.21	1.79	3.09	7.33	13.13	24.62	551
Industry Avg.	2,350.5	1.68	2.37	3.33	3.47	8.50	-1.20	
p-value	0.00	0.00	0.02	0.14	0.00	0.28	0.00	
BW (exc. IWS)	28,993.2	2.33	3.23	2.45	6.57	10.22	26.01	565
Industry Avg.	2,745.9	1.71	2.64	3.27	3.76	13.04	1.44	
p-value	0.00	0.00	0.07	0.00	0.00	0.71	0.00	
Forbes	24,105.7	1.78	4.26	1.97	3.68	15.40	15.69	791
Industry Avg.	2,594.4	1.42	3.05	2.97	3.92	13.03	3.52	
p-value	0.00	0.00	0.00	0.00	0.49	0.16	0.00	
Fortune	33,824.9	2.58	2.66	2.80	12.13	33.66	45.24	596
Industry Avg.	2,970.9	1.79	7.50	3.53	4.07	12.13	7.22	
p-value	0.00	0.00	0.01	0.00	0.00	0.06	0.00	

Panel B: Recommendation Style and Content by Source

Source	Direct Rec.	Refers to Analyst	Refers to Investor	Refers to Mgmt.	Merger & Acquisition	Product News	Obs.
Inside Wall Street	0.0%	58.8%	44.1%	6.9%	27.2%	25.2%	551
Business Week (Exc. IWS)	8.3%	42.8%	43.0%	0.7%	1.8%	5.0%	565
Forbes	91.7%	6.3%	2.1%	0.0%	1.0%	0.1%	791
Fortune	44.7%	36.3%	17.6%	0.5%	2.5%	4.4%	596

Panel C: Confounding Announcements and Analyst Output by Source

Source	Other Columnist Recom.	Earnings Annc.	Analyst Earnings Forecast	Analyst Recom.	Analyst Consensus Recom. Rating	Analyst Following	Obs.
Inside Wall Street	5.0%	6.4%	18.5%	14.9%	2.05	4.15	551
Business Week (Exc. IWS)	1.2%	2.5%	29.9%	19.1%	2.16	7.57	565
Forbes	0.8%	5.8%	29.8%	19.5%	2.23	6.11	791
Fortune	2.0%	8.4%	35.1%	22.7%	2.02	7.62	596

Table 1.5 Regression Analysis of Publication Returns

All continuous independent variables are winsorized at the top and bottom one percentile. *t*-statistics, based on Huber-White standard errors clustered by firm, are reported in parentheses below the coefficients. *, indicates significance at the 10 percent significance level, **, indicates significance at the 5 percent significance level and ***, indicates significance at the 1 percent significance level. The final four rows report F-value, R-square, adjusted R-square and number of observations.

	Model I	Model II	Model III	Model IV
IWS	0.024***	0.022***	0.019***	0.019***
	(5.94)	(4.74)	(3.45)	(3.49)
SPREAD	0.274**	0.283**	0.278**	0.279**
	(2.20)	(2.25)	(2.22)	(2.22)
CAR(-10,-2)	-0.017	-0.018	-0.022	-0.022
	(-0.65)	(-0.68)	(-0.85)	(-0.86)
FOR_STD	-0.006	-0.006	-0.006	-0.006
	(-0.76)	(-0.71)	(-0.74)	(-0.74)
RND	-0.001	-0.001	-0.001	-0.001
	(-0.39)	(-0.40)	(-0.25)	(-0.25)
SIZE	-0.002**	-0.002**	-0.002**	-0.001*
	(-2.34)	(-2.34)	(-2.23)	(-1.69)
DIRECT		-0.003	-0.001	-0.001
		(-0.57)	(-0.21)	(-0.16)
REF_ANLYST		-0.002	-0.000	-0.000
		(-0.41)	(-0.05)	(-0.04)
REF_INV		0.000	0.002	0.002
		(0.03)	(0.32)	(0.32)
REF_MGMT		0.030*	0.031*	0.031*
		(1.65)	(1.66)	(1.65)
MERGER_NEWS			0.021***	0.021***
			(3.03)	(3.06)
PRODUCT_NEWS			-0.011	-0.011
			(-1.38)	(-1.39)
CNFDG				-0.005
				(-1.58)
Constant	0.030**	0.032**	0.029**	0.025*
	(2.29)	(2.31)	(2.09)	(1.82)
Fama and French 49 Industry Fixed Effects	Yes	Yes	Yes	Yes
F-Value	8.954***	5.948***	6.632***	6.150***
R^2	5.6%	5.9%	6.5%	6.6%
Adjusted R^2	3.3%	3.5%	4.0%	4.1%
Obs.	2,291	2,291	2,291	2,291

Table 1.6 Long Term Performance of Recommendations

This table reports average monthly abnormal return and factor sensitivities of portfolios formed according to (1) all columnist recommendations, (2) financial analysts' upgrades, (3) Inside Wall Street recommendations, (4) Business Week excluding IWS recommendations, (5) Forbes recommendations and (6) Fortune recommendations. Panel A reports results for portfolios formed with a one-day trading delay and Panel B reports results for portfolios formed without a trading delay.

Sample	Intercept	Beta	SMB	HML	UMD	Adjusted R-Square
Panel A: One-day trading delay						
All Columnist Recommendations	-0.313	0.998	-0.168	-0.331	-0.062	81.9%
t-ratio	(-0.79)	(10.96)	(-1.79)	(-3.03)	(-1.12)	
t-ratio (Robust)	(-0.71)	(9.2)	(-1.27)	(-2.72)	(-0.69)	
Financial Analysts' Upgrades	-0.151	1.018	-0.059	-0.133	-0.096	96.6%
t-ratio	(-0.98)	(28.54)	(-1.63)	(-3.12)	(-4.3)	
t-ratio (Robust)	(-1.26)	(33.1)	(-2.22)	(-3.29)	(-6.46)	
Inside Wall Street	-0.113	0.902	-0.003	-0.416	-0.110	70.4%
t-ratio	(-0.2)	(7)	(-0.02)	(-2.69)	(-1.41)	
t-ratio (Robust)	(-0.2)	(6.63)	(-0.02)	(-2.83)	(-0.97)	
Business Week Excluding IWS	0.181	0.946	0.224	-0.595	0.044	80.8%
t-ratio	(0.37)	(8.25)	(1.93)	(-4.33)	(0.61)	
t-ratio (Robust)	(0.46)	(9.98)	(1.56)	(-3.98)	(0.49)	
Forbes	-0.020	0.975	-0.236	-0.067	-0.122	87.2%
t-ratio	(-0.07)	(14.6)	(-3.45)	(-0.84)	(-3.01)	
t-ratio (Robust)	(-0.07)	(12.73)	(-2.87)	(-0.94)	(-2.58)	
Fortune	-0.379	1.108	-0.194	-0.593	0.074	70.6%
t-ratio	(-0.6)	(7.59)	(-1.3)	(-3.39)	(0.84)	
t-ratio (Robust)	(-0.55)	(6.29)	(-0.91)	(-2.97)	(0.56)	

Sample	Intercept	Beta	SMB	HML	UMD	Adjusted R-Square
Panel B: No trading delay						
All Columnist Recommendations	-0.294	0.957	-0.136	-0.316	-0.086	79.6%
t-ratio	(-0.71)	(10)	(-1.39)	(-2.76)	(-1.48)	
t-ratio (Robust)	(-0.61)	(8.25)	(-1)	(-2.33)	(-0.85)	
Financial Analysts' Upgrades	1.204	0.648	0.213	-0.250	-0.180	17.4%
t-ratio	(0.88)	(2.05)	(0.66)	(-0.66)	(-0.91)	
t-ratio (Robust)	(1.08)	(1.69)	(0.78)	(-1.9)	(-1.44)	
Inside Wall Street	0.015	0.916	0.018	-0.421	-0.086	68.4%
t-ratio	(0.02)	(6.72)	(0.13)	(-2.58)	(-1.05)	
t-ratio (Robust)	(0.03)	(6.33)	(0.08)	(-2.76)	(-0.73)	
Business Week Excluding IWS	0.213	0.954	0.221	-0.595	0.049	82.2%
t-ratio	(0.45)	(8.69)	(1.98)	(-4.52)	(0.71)	
t-ratio (Robust)	(0.57)	(10.77)	(1.56)	(-4.01)	(0.57)	
Forbes	0.012	0.968	-0.227	-0.057	-0.128	88.0%
t-ratio	(0.04)	(15.08)	(-3.46)	(-0.74)	(-3.3)	
t-ratio (Robust)	(0.04)	(13.12)	(-2.81)	(-0.83)	(-2.76)	
Fortune	-0.501	1.104	-0.180	-0.573	0.059	66.9%
t-ratio	(-0.73)	(6.99)	(-1.11)	(-3.03)	(0.61)	
t-ratio (Robust)	(-0.68)	(5.83)	(-0.82)	(-2.71)	(0.4)	

Table 1.7 Characteristics of Direct and Indirect Recommendations

This table provides descriptive statistics by recommendation type: direct and indirect. The first column in both panels A and B indicate the recommendation type. The following columns in panel A report the market value calculated using CRSP data (in millions), previous year's raw return and previous year's turnover ratio calculated as the sum of trading volume divided by the average shares outstanding. The remaining columns in panel A report the short term CAARs (-40, -2), (-20,-2), (-10,-2) and (-5,-2) of the two recommendation types. Panel B reports the mean parameters of the four-factor model estimated separately for each firm using previous year's daily return data. For ease of interpretation the alpha is annualized. Finally the last two columns report the mean analyst following and the consensus recommendation rating. The third rows in both panels report *p*-values of mean difference test statistics between direct and indirect recommendations.

Panel A: Market Value, Liqudity and Abnormal Returns by Recommendation Type

Recommendation Type	Market Value	Previous Year's Return	Previous Year's Turnover Ratio	CAAR (-40, -2)	CAAR (-20, -2)	CAAR (-10, -2)	CAAR (-5, -2)	Obs.
Indirect	23,306.1	46.2%	2.4	0.69%	0.92%	0.77%	0.48%	1,456
Direct	27,171.1	18.2%	2.2	-1.74%	-1.29%	-0.27%	0.23%	1,047
p-value	0.10	0.00	0.17	0.01	0.00	0.01	0.36	

Panel B: Risk Parameters and Analyst Data by Recommendation Type

Recommendation Type	Alpha	Beta	SMB	HML	UMD	Analyst Following	Rec. Rating Consensus	Obs.
Indirect	27.8%	1.103	0.442	0.174	-0.077	6.21	2.07	1,456
Direct	15.3%	1.032	0.231	0.174	-0.061	6.48	2.20	1,047
p-value	0.00	0.00	0.00	1.00	0.51	0.21	0.00	

Table 1.8 Long Term Performance of Direct and Indirect Recommendations

This table reports average monthly abnormal return and factor sensitivities of portfolios formed according to (1) indirect recommendation and (2) direct recommendations. Panel A reports results for portfolios formed with a one-day trading delay and Panel B reports results for portfolios formed with no trading delay.

Sample	Intercept	Beta	SMB	HML	UMD	Adjusted R-Square
Panel A: One-day Trading Delay						
Indirect Recommendations	-0.411	1.081	-0.115	-0.439	0.011	72.9%
t-ratio	(-0.73)	(8.3)	(-0.86)	(-2.81)	(0.14)	
t-ratio (Robust)	(-0.71)	(7.19)	(-0.59)	(-2.67)	(0.1)	
Direct Recommendations	-0.018	0.980	-0.223	-0.285	-0.058	88.7%
t-ratio	(-0.06)	(14.89)	(-3.3)	(-3.62)	(-1.46)	
t-ratio (Robust)	(-0.06)	(12.29)	(-2.28)	(-3.78)	(-1.23)	
Panel B: No Trading Delay						
Indirect Recommendations	-0.538	1.077	-0.102	-0.413	-0.001	68.3%
t-ratio	(-0.86)	(7.48)	(-0.69)	(-2.39)	(-0.02)	
t-ratio (Robust)	(-0.84)	(6.45)	(-0.5)	(-2.32)	(-0.01)	
Direct Recommendations	-0.001	0.960	-0.210	-0.277	-0.070	88.5%
t-ratio	(0.01)	(14.58)	(-3.12)	(-3.51)	(-1.75)	
t-ratio (Robust)	(0.01)	(11.95)	(-2.15)	(-3.57)	(-1.45)	

1.7 Figures for Chapter 1

Figure 1.1 Short Term Market Reaction to Recommendations

The x-axis indicates the number of days relative to recommendation's publication date. The y-axis represents the average abnormal return cumulated starting 15 days before the recommendation's publication date up to the corresponding day on the x-axis. Abnormal returns are computed using the four-factor model with the CRSP value-weighted index as the market index. Six separate running cumulative average abnormal return series are illustrated for: (1) the Inside Wall Street (IWS) column, (2) Business Week excluding IWS, (3) Forbes, (4) Fortune, (5) all columnists (BW, Forbes and Fortune), and (6) financial analysts' upgrades.

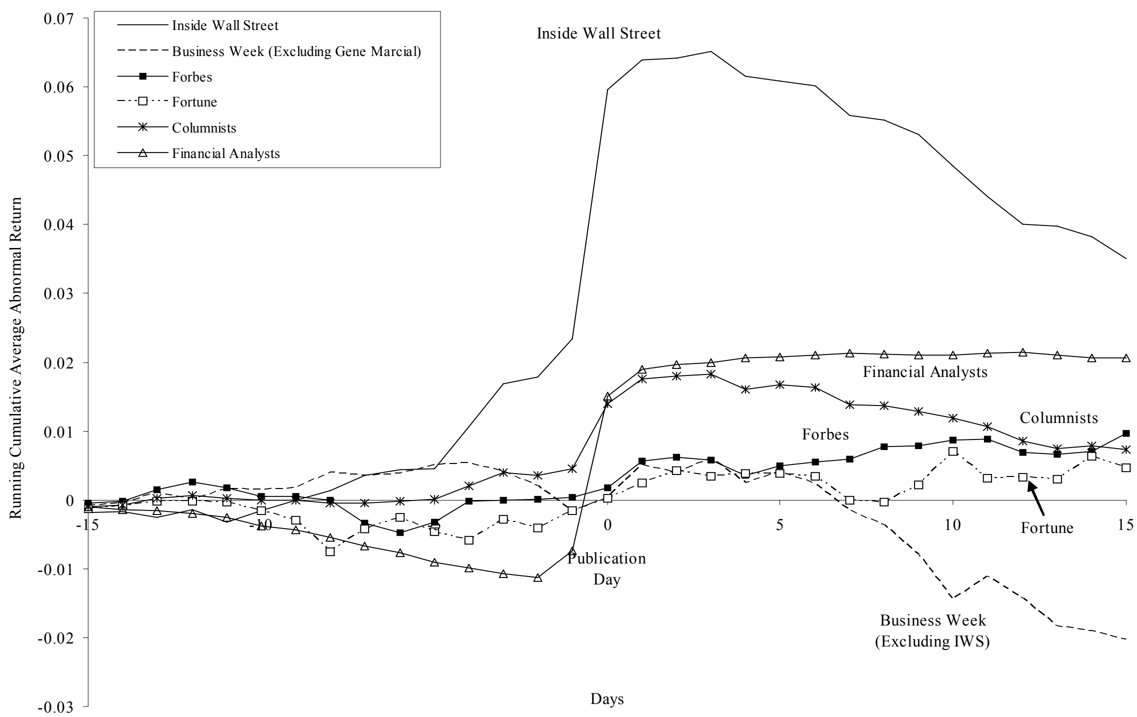
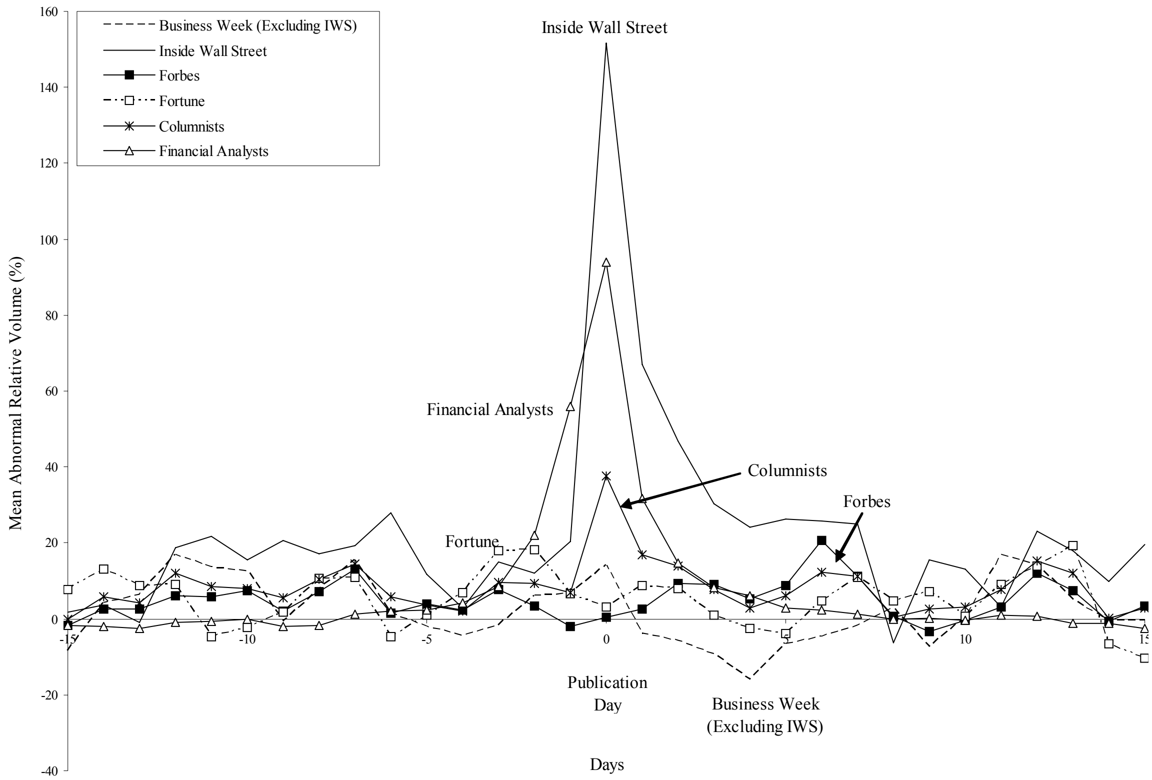


Figure 1.2 Trading volume reaction to recommendations
The x-axis indicates the number of days relative to recommendation-publication-day. Abnormal relative volume is calculated each day for: (1) the Inside Wall Street (IWS) column, (2) Business Week excluding IWS, (3) Forbes, (4) Fortune, (5) all columnists (BW, Forbes and Fortune), and (6) financial analysts' upgrades.



Chapter 2 R&D Intensity and the Value of Analysts' Recommendations

2.1 Introduction

This essay investigates the relation between the value of analysts' recommendation revisions and firms' research and development (R&D) investments. To the extent that R&D investments introduce greater information asymmetry between managers and shareholders, R&D intensive firms are likely to have less informative share prices absent analyst coverage.[1] R&D investments may introduce greater information asymmetry than investment in capital or financial inputs, for a number of reasons. R&D projects tend to be unique to the firm that is invested in them, whereas capital and financial investments (e.g., purchase of ships, airplanes, factories, and equity) share common attributes across firms. This makes it more difficult for investors to derive inferences about one R&D intensive firm based on another. Further, unlike physical or financial investments, R&D investments are not traded in organized markets where one can obtain information on the productivity and value of R&D investments. Finally, U.S. GAAP requires R&D investments to be expensed immediately, preventing financial reporting on the value and productivity of R&D investments.[2] Within such an environment where information asymmetry is pronounced, analysts who are specialized in private information acquisition

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[1] For example, Aboody and Lev (1998), Chan, Lakonishok and Sougiannis (2001) and Lev, Sarath and Sougiannis (2005) find evidence consistent with mispricing of the shares of R&D intensive companies.

[2] Two exceptions are software development (SFAS 86) and oil and gas exploration costs (SFAS 69).

and information processing activities have the potential to detect greater levels of mispricing.

On the other hand, greater information asymmetry prevailing in R&D intensive firms can prevent analysts from deriving accurate inferences and hamper the value of their recommendations. Information complexity, fundamental uncertainty and lack of public information may increase the difficulty analysts experience when processing information and adversely affect the value of their recommendation revisions. For example, Gu and Wang (2005) find analysts' earnings forecast accuracy to be significantly lower for intangible intensive firms. The conflicting forces at work here call for an empirical examination of the relation between the value of analysts' recommendations and corporate R&D investments.

The examination of the relation between the value of analysts' recommendations and firms' R&D investments is important for several reasons. First, assuming that R&D investment is a source of information asymmetry, the analysis of the relation between R&D investments and the value of analysts' recommendations reveals evidence on whether analysts, who are specialized in private information acquisition activities, are able to detect mispricing for firms with greater levels of information asymmetry. Accordingly, the results present indirect evidence on the determination of analysts' comparative advantage (e.g., information acquisition or interpretation of public information). Second, from an accounting standpoint, this paper provides evidence on the relation between the level of accounting information and analyst reports' informativeness. Despite the absence of financial recognition of R&D investments, there is evidence (Lev and Sougiannis (1996)) demonstrating that security prices, to some extent, impound the future benefits of R&D investments. This essay sheds light on the role of analysts in the market mechanism through which investors incorporate the value and productivity of R&D investments to prices. Further, this essay's analysis, by providing a relative assessment of the value of analysts for R&D intensive firms compared to low-R&D intensive firms, presents important results for managers of R&D companies interested in gauging the relative market impact of recommendations.

This essay examines the relation between the value of analysts' recommendations and R&D expenditures through univariate, calendar-time portfolio regression and cross-sectional analyses. In the first two analyses, I categorize each firm-year into quintiles based on R&D intensity (R&D expense scaled by sales).[3] The first quintile contains firms with the least R&D intensity and the fifth quintile contains firms with the greatest R&D intensity. In the univariate analysis, I investigate the average abnormal market reaction associated with analysts' recommendation revisions (e.g., upgrades and downgrades) for several short-term event windows. I then examine the statistical significance of the difference in returns between top and bottom R&D quintiles to test whether financial analysts' recommendation revisions are associated with significantly different market reactions for firms that are heavily engaged in R&D projects.

In the calendar-time portfolio regression approach, I construct separate buy and sell portfolios within each R&D quintile based on analyst recommendation revisions. Each upgraded (downgraded) firm is held in a long (short) portfolio for one year unless the analyst revises the recommendation earlier. I then estimate the value of analysts'

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[3] I use the distribution of R&D expenditures of firms that report R&D expenditures to classify all firms into R&D quintiles.

recommendation revisions for each R&D quintile as the average monthly abnormal return (Jensen's alpha) that accrues to a hedge portfolio that goes long on upgraded and short on downgraded stocks. Finally, using a portfolio that goes long on the hedge portfolio for the top R&D quintile and short on the hedge portfolio for the bottom R&D quintile firms, I estimate and test the difference in the value of analysts' recommendations between top and bottom R&D quintile firms. While estimating the Jensen's alpha, I control for market risk, size, book-to-market and momentum effects. Finally, I conduct a cross-sectional analysis to examine the relation between the value of recommendation revisions and R&D expenditures while controlling for firm risk, business complexity, earnings value-relevance, analyst coverage, institutional ownership and bid-ask spread.

The empirical results *consistently* indicate that analysts' recommendation revisions are more valuable for firms that are heavily engaged in R&D investments than for firms that do not have significant R&D investments. Specifically, the univariate analysis suggests that analysts' upgrades for firms in the top R&D quintile are associated with 2.3 percent higher cumulative average abnormal returns (CAAR) than their upgrades for firms in the bottom R&D intensity quintile. Similarly, the return differential for downgrades, between top and bottom R&D quintiles, is 3.57 percent which corresponds to a statistically and economically significant difference. The results are similar when controlling for various other confounding factors such as market risk, book-to-market, size, momentum, business complexity, earnings value-relevance, analyst coverage, institutional ownership and the bid-ask spread through the calendar-time portfolio and cross-sectional analysis.

This study contributes to the literature that examines financial analysts in relation to intangible assets. Prior studies in the area investigate analysts' incentives to cover intangible intensive firms (Barth, Kasznik and McNichols (2001)), analysts' earnings forecast for R&D intensive firms (Gu and Wang (2005)) and the relative emphasis that analysts give to their own private information when forecasting high-tech firms' earnings (Barron, Byard, Kile and Riedl (2002)). However, there is no evidence on the relation between the value of analysts' recommendations and R&D investments. I add to the existing literature by examining whether the value of analysts' recommendation revisions is different for firms with different levels of R&D investments. In addition, I add on to the literature that examines the determinants of the value of analysts' reports (Francis, Schipper and Vincent (2002) and Frankel, Kothari and Weber (2006)) by providing evidence on the relation between the value of recommendation revisions and R&D expenditures. Finally, this study contributes to the understanding of R&D investments and their impact on users' (e.g., analysts) processing of information. Prior studies argue that expensing R&D investments decreases the usefulness of financial reports (Lev and Sougiannis (1996), Lev and Zarowin (1999) and Luft and Shields (2001)). I find evidence that suggests analysts provide more informative stock recommendations for R&D intensive firms, which potentially reduces the adverse effect of less useful financial reports.

2.2 Literature Review and Hypothesis Development

Corporate investment, in general (regardless of whether it is on R&D), creates greater information asymmetry because managers have the ability to continuously monitor and influence productivity at an individual asset basis, whereas outsiders obtain only aggregated performance results that are generally reported quarterly. R&D investments, however, introduce greater level of information asymmetry than other investments because R&D is primarily carried out to achieve firm-uniqueness (Titman and Wessels (1988)). Pharmaceutical firms invest in R&D to develop new drugs that their competitors do not produce. Software firms expend effort to create more useful software that their counterparts do not have and other firms in various industries invest in R&D to distinguish their products or services from their competitors. Hence, corporate investment in R&D causes firms to become more distinct. In addition, R&D investments involve substantial uncertainty about the outcome of projects which complicates the task of arriving at reliable estimates. Kothari, Laguerre and Leone (2002) find that R&D investments generate future benefits that are three times more uncertain than those generated by capital investments.

Further, while investors can obtain information on tangible/financial investments' productivity through various sources including other firms' performances, industry-wide developments and macroeconomic trends, public information on R&D intensive firms is relatively scarce and investors are generally limited to corporate disclosure to assess the performance of R&D investments.[4] For instance, to gauge the current value of a firm's real estate investment an investor can examine developments in the broad real estate market and arrive at an estimate. On the other hand to estimate the productivity and value

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[4] One exception is when two or more firms that applied for a patent are competing to develop the same product. In such a case, the patent approval news of one firm may imply the failure of the other firms. Another scenario where investors can gather information about a particular R&D firm from another firm is when the approval/rejection decision of a regulatory organization reveals more information about the standards and requirements that apply to all firms in the industry.

of a firm's particular R&D project, one cannot rely on broad market measures and is therefore limited to rely on firm-specific information.

In addition, there is no organized market where R&D investments are traded. Investors, therefore, cannot benefit from the presence of a market value for a unit of R&D investment. This is less of a concern for tangible and financial investments. Investors can obtain information based on the resale price of tangible assets and the market price of financial instruments that are mostly being traded in organized markets. The absence of a market-based price for R&D investments increases the level of information asymmetry associated with R&D intensive firms.

Finally, U.S. GAAP (SFAS 2) requires all R&D investments to be expensed in financial reports. Hence, corporations are not required to report information on the value or productivity of the R&D projects that they are investing in. On the other hand, U.S. GAAP requires corporations to periodically mark-to-market their financial assets and write down or write-up (up to the historical cost, adjusted for depreciation) the value of their tangible assets. As a result, accounting rules intensify the information asymmetry associated with R&D firms.

Managers can reduce information asymmetry by communicating information about the productivity and value of their R&D project through voluntary disclosure. However, voluntary disclosure is unlikely to completely eliminate the information asymmetry differential between non-R&D and R&D intensive firms because (1) voluntary disclosures are not audited; (2) it is more costly to extract useful information from voluntary disclosure as opposed to recognized amounts in financial statements and

(3) managers may be reluctant to fully voluntarily disclose information because of competitive and/or litigation reasons (Bhattacharya and Ritter (1983), Anton and Yao (2002)).

Empirical evidence on R&D and information asymmetry. Prior evidence highlights R&D investments as an important source of information asymmetry which is exacerbated by current accounting principles. Amir and Lev (1996) find non-financial information in the wireless communications industry to be highly important whereas financial information to be largely irrelevant for security valuation. In addition, Lev and Zarowin (1999) document a significant decline in the value-relevance of financial statements amid the emergence of intangible intensive firms. They attribute the decline in the relevance of financial statements to reporting deficiencies and call for an extended capitalization of intangible investments. Mohd (2005) investigates the impact of SFAS 86 on information asymmetry and finds a substantial decline for software companies relative to other R&D intensive companies.

Aboody and Lev (2000) find insider gains in R&D intensive firms to be significantly greater than insider gains in firms without R&D investments. In addition, Boone and Raman (2001) by investigating the adverse selection component of the bid-ask spread and depth find information asymmetry to be positively associated with R&D capital. Barth and Kasznik (1999) report findings that show R&D investments to be positively related to share repurchases, which suggests higher information asymmetry for R&D intensive firms.

R&D and financial analysts. The greater information asymmetry between shareholders and managers increases the need for private information acquisition. Barth, Kasznik and McNichols (2001) find that analyst coverage is significantly greater for R&D intensive firms and analysts expend more effort to cover such firms. Tasker (1998) finds that R&D intensive firms conduct more conference calls than low R&D intensity firms and attribute this to analysts' greater demand for information. Overall, prior evidence suggests that investors and analysts demand more information and allocate more resources to understand R&D intensive firms. An unanswered question is whether analysts, amid greater allocation of resources, are able to make informative recommendations for R&D intensive firms.

Analyst recommendations and the source of their advice. The prior literature on analyst recommendations suggests that analysts, in general, make informative stock recommendations. Bjerring, Lakonishok and Vermaelen (1983), Womack (1996), Barber, Lehavy, McNichols and Trueman (2001) and others find significant abnormal returns that accrue to analyst recommendations in the short and long term. These results are consistent with analysts possessing private information and/or superior information processing ability. Financial analysts' ability to interpret information and acquire private information sets them apart as a key source of advice for individual and institutional investors.

Prior evidence indicates that the main source of analysts' value is analysts' ability to acquire and interpret private information. Ivkovic and Jegadeesh (2004) use quarterly earnings releases as a proxy for the level of public information and investigate the value and timing of analysts' stock recommendations. They find that analysts' interpretation of information in quarterly earnings announcements is not the dominant source of analysts' value and that more value is derived from analysts' independent collection of information.

For technology-intensive firms, prior findings suggest that analysts rely more on private information. Barron, Byard, Kile and Riedl (2002) find that analysts, when projecting future earnings of firms with greater research and development expenditures, supplement firms' financial information by placing greater emphasis on private information. Abdolmohammadi, Simnett, Thibodeau and Wright (2006) find that analysts, for companies that rely heavily on technology and intangible assets, tend to supplement their analysis with nonfinancial information that is not necessarily available in the financial statements. Analysts' emphasis to private information for high-tech firms highlights analysts as agents who can exploit the greater level of information asymmetry present in R&D intensive firms and make more valuable recommendations.[5]

On the other hand, financial analysts face greater challenges when projecting R&D intensive firms' future cash-flows and interpreting information. Gu and Wang (2005) find analysts' earnings forecast accuracy to be significantly lower for intangible intensive firms. Gu and Wang's evidence suggests that information asymmetry is not fully mitigated through higher analyst coverage & effort and that analysts' performance (i.e. earnings forecast accuracy) suffers amid the intangible intensive nature of firms.

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[5] In equilibrium there is likely to be a return differential between recommendations for low and high R&D firms because analyst effort/coverage would increase up to the point that recommendations' marginal productivity equals marginal cost which for R&D intensive firms is likely to be higher because of the complexity of the business and the level of information asymmetry involved in R&D intensive firms.

Further, the empirical and theoretical judgment/decision-making literature posits that task complexity adversely affects judgment quality. Plumlee (2003) finds results consistent with analysts underweighting the importance of more complex information and assimilating less complex information. To the extent that R&D firms are associated with more complex information; analysts are less likely to make accurate inferences about the fair value of R&D firms, their investments and therefore provide less valuable recommendations.

Hypothesis. The presence of greater information asymmetry in R&D intensive firms and the challenges analysts face in analyzing R&D intensive firms are conflicting forces at play. On the one hand, analysts for R&D intensive firms have the potential to detect greater levels of mispricing and make more valuable recommendations due to the greater level of information asymmetry. On the other hand, R&D intensive firms have more uncertain future cash-flows, provide less information and are involved in considerably more complex operations. Ex ante, it is unclear which of the conflicting forces dominates the other. I therefore hypothesize the value of recommendations to not be different for low- and high- R&D intensive firms.

H_0: The value of analysts' stock recommendations is not different for high and low R&D intensive firms.

2.3 Research Design

This paper examines the relation between R&D expenditures and the value of analysts' recommendations through three separate analyses: univariate, calendar-time portfolio and cross-sectional. The univariate analysis provides an overview of the market impact associated with recommendation revisions for firms with different levels of R&D

expenditures. The drawback of this analysis is that it does not control for factors that affect returns and may be associated with R&D expenditures. In the calendar-time portfolio regression analysis I examine the value of analysts' recommendations while controlling for beta, size, book-to-market and momentum factors which are well established in the finance literature to explain the cross-section of returns. Finally, in the cross-sectional analysis I control for other firm-specific attributes including business complexity, earnings value-relevance, analyst coverage, institutional ownership and bid-ask spread which may affect the value of recommendations.

2.3.1 Univariate Analysis

This essay uses recommendation revisions as the basis for measuring the value of analysts' recommendations. I compute the ratio of R&D expenditure and sales for each firm-year to proxy for R&D investment intensity.[6] Based on the R&D intensity distribution of firms that report R&D expenditures I construct quintiles of firms increasing in R&D intensity. To classify recommendation revisions to different R&D quintiles, I use a firm's R&D quintile assignment based on fiscal year t, three-months after the fiscal year-end (t) until the end of the third month after the fiscal year-end of year t+1. This avoids any hindsight bias from influencing the results.

In the univariate analysis I compute cumulative abnormal returns of recommendations revisions for the event windows: (-1, +1), (-2, +2), (0, +1), (0, +5), (0, +10) and (0, +20). To compute abnormal returns, I match each revised firm to a exchange

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[6] Forming R&D quintiles based on a capitalized measure of R&D expenditures yields similar results. Because capitalization requires up to four-years of historical financial statement data I report results based on the ratio of R&D expenditures and sales.

and size decile portfolio using the CRSP-reported exchange and decile number as of the revision date. I compute the difference between the revised firm's raw return and the matched size-exchange portfolio's return as an estimate of abnormal return:

$$\mathrm{CAR}_i(T_1, T_2) = \sum_{t=T_1}^{T_2} \mathrm{ret}_{it} - \sum_{t=T_1}^{T_2} \mathrm{ret}_{bt},$$

where ret_{it} is the return on security i on day t and ret_{bt} is the return on the matched exchange and size decile return on day t, T_1 is the return accumulation begin-day relative to the recommendation revision and T_2 is the end-date.

For robustness, I replicate the analysis using several abnormal measurement methods including, market-adjusted returns, market, Fama & French three-factor and Carhart four-factor model returns and experiment with various reference market portfolios including the CRSP equal-weighted, CRSP value-weighted, and S&P 500 indice returns. Consistent with findings reported by Brown and Warner (1985), short-term return results are mainly insensitive to the choice of abnormal return measurement model and choice of reference portfolio. Therefore, for brevity, I report results based on size & exchange adjusted returns. The main advantage of this approach is that, similar to a market adjustment method, this method does not require prior data but additionally adjusts for returns common to the size and exchange (e.g. NYSE, AMEX, Nasdaq).

I compute cumulative average abnormal returns (CAAR) by quarter and R&D quintile. This procedure yields 48 quarterly CAARs per quintile for the fiscal years 1993-2004. Then using the Fama Macbeth approach (with Newey and West (1987) lag-4 correction) I test for the significance of CAARs and the differences in CAARs between top and bottom R&D quintile firms.

2.4 Calendar-Time Portfolio Regression Approach

In the calendar-time portfolio regression analysis I estimate analyst recommendation revisions' long-term impact on firm value for different R&D quintiles and test whether this impact is different between top and bottom R&D quintile firms. In order to measure the long-term impact of revisions I conduct the calendar-time portfolio regression approach which is commonly used in the accounting and finance literatures to measure long-term security performance (Jaffe (1974), Sloan (1996) and Fama (1998)). It is important to note that different from prior studies the emphasis with this analysis is not to test a possible trading strategy that can be used to earn abnormal returns but rather to understand the long-term impact of analyst revisions on firm value. This approach complements the univariate analysis which focuses on short-term returns by looking at a longer period extending up to one year.[7]

Based on prior year's R&D intensity quintile cut-off levels I classify all firms into R&D quintiles increasing in R&D intensity. Then using analyst recommendation revisions, I form short and long portfolios within each R&D quintile. An upgraded firm is placed in the long portfolio and a downgraded firm is placed in the short portfolio. The efficient market hypothesis posits that all public information instantaneously becomes impounded in prices. Therefore, to fully capture the information conveyed by analysts'

[7] To estimate long-term abnormal returns I use calendar-time portfolio regression approach because using the methodology executed in the univariate analysis is likely to yield biased results (Brown and Warner (1980) and Mitchell and Stafford (2000)).

revisions I place a revised firm into the respective portfolio on the day of the recommendation revision.[8] Once a firm enters a portfolio it remains in the portfolio for one year unless it is revised by the same analyst. Since a firm-year may enter the same portfolio multiple times, observations across periods can no longer be assumed to be independent. I therefore compute Newey and West (1987) (one-year lag) corrected standard errors.

The construction of short and long portfolios within each R&D quintile yields five short and five long portfolios. I calculate the daily equal- and value-weighted returns for the ten portfolios on day *t* as follows:

$$EW_{pt} = \frac{1}{n_{p,t}} \sum_{m=1}^{n_{p,t-1}} R_{m,t},$$

$$VW_{pt} = \frac{\sum_{m=1}^{n_{p,t}} \left(R_{m,t} \times mv_{m,t-1} \right)}{\sum_{m=1}^{n_{p,t}} mv_{m,t-1}}$$

where EW_{pt} and VW_{pt} are, respectively, equal- and value- weighted portfolio returns on day t, $R_{m,t}$ is day t return on security m, $n_{p,t}$ is the number of firms in the portfolio and

[8] Constructing portfolios on the day of the recommendation revision date assumes foreknowledge of the recommendation revision and makes the strategy difficult for an outsider to implement. Therefore the empirical results do not suggest an anomaly or market inefficiency that can be arbitraged by investors. In untabulated analysis, I also estimate abnormal returns to portfolios that are constructed with one-day lag and find that the abnormal returns associated with recommendation revisions disappears when an investor trades with a lag.

$mv_{m,t-1}$ is the market value of firm *m* on day *t-1*. For brevity, in the remainder of this section I denote equal- and value-weighted portfolio returns with the general symbol R_{pt}.

To the extent analysts make informative recommendation revisions, upgrades (downgrades) are expected to be associated with positive (negative) returns. Therefore the return differential between long and short portfolios can be considered an estimate of the overall value of analysts' recommendation revisions. To measure and test the significance of this return differential, for each R&D quintile I construct a hedge portfolio that combines short and long portfolios. This portfolio simultaneously takes long positions in upgraded and short positions in downgraded firms. The average abnormal return of this hedge portfolio gives an estimate of the overall value of recommendation revisions for each R&D quintile. Finally, to test whether the value of recommendation revisions is significantly different between top and bottom R&D quintiles I construct an additional portfolio that goes long on the hedge portfolio for the top R&D quintile and short on the hedge portfolio for the bottom R&D quintile. The average abnormal return that this portfolio accrues provides an estimate of the difference in the value of recommendation revisions between top and bottom R&D quintile firms.

I report raw monthly returns and abnormal monthly returns based on three asset pricing models: CAPM, three-factor and four-factor models. To estimate CAPM abnormal returns, I estimate the time-series regression below and use the intercept, α_p (Jensen's alpha), as an estimate of the mean abnormal daily return of portfolio *p*:

$$\mathrm{R_{pt}} - \mathrm{rf_t} = \alpha_p + \beta_p\left(\mathrm{Mkt_t} - \mathrm{rf_t}\right) + \varepsilon_{pt},$$

where R_{pt} is the raw portfolio return of portfolio *p* on day *t*, rf_t is the risk-free rate for day *t*, Mkt_t is the CRSP value-weighted market return. Third, I estimate the Fama and French (1993) three-factor model:

$$R_{pt} - rf_t = \alpha_p + \beta_p(Mkt_t - rf_t) + s_p SMB_t + h_p HML_t + \varepsilon_{pt},$$

where SMB_t is the average return on the three small portfolios (value, neutral and growth) minus the average return on the three big portfolios (value, neutral and growth) on day *t*, HML_t is the average return on the two value portfolios (small and big) minus the average return on the two growth portfolios (small and big) on day *t*. Finally, I estimate the Carhart (1997) four-factor model:

$$R_{pt} - rf_t = \alpha_p + \beta_p(Mkt_t - rf_t) + s_p SMB_t + h_p HML_t + u_p UMD_t + \varepsilon_{pt},$$

where UMD_t is the average return on the two high prior return portfolios (small and big) minus the average return on the two low prior return portfolios (small and big).[9] To address the possibility that nonsynchronous trading affects the results, I include one lag of each independent variable (Mkt-rf, SMB, HML and UMD) in all three model estimations (Scholes and Williams (1977)). In all estimations the intercept, α_p (Jensen's Alpha), is an estimate of the average daily abnormal return associated with the portfolio. For ease of interpretation I multiply alphas by 20 and report monthly average returns.

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[9] Fama and French (1993) construct the six portfolios used in the calculation of SMB and HML factor returns at the end of each June using the intersections of two portfolios (small and big) formed on size (market equity) and three portfolios (value, neutral and growth) formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in t-1 divided by ME for December of t-1. The BE/ME breakpoints are the 30th and 70th NYSE percentiles.

2.5 Cross-Sectional Analysis

It is possible that the value of recommendation revisions is affected by factors other than market risk, size, book-to-market and momentum effects. Using a cross-sectional analysis, I examine the relation between the value of analysts' recommendation revisions and R&D intensity controlling for business complexity, earnings value-relevance, analyst coverage, institutional ownership and the bid-ask spread.

To measure the value of recommendation revisions for each firm-year I first compute the two-day abnormal market reaction associated with each recommendation revision.

$$\mathrm{CAR}(0,1)_{i,t,j} = \sum_{d=0}^{1} \mathrm{ret}_{i,t,j,d} - \sum_{d=0}^{1} \mathrm{ret}_{b,t,j,d}$$

where $\mathrm{ret}_{i,t,j,d}$ is the raw return of firm *i*'s shares on day *d* in response to the *jth* recommendation revision made during the year *t* and $\mathrm{ret}_{b,t,j,d}$ is the benchmark return (based on size decile and exchange) for day *d*. Upgrades are expected to be associated with positive and downgrades are expected to be associated with negative returns. To account for the difference in signs of expected returns I multiply downgrades' cumulative abnormal returns by -1. This adjustment aligns downgrades and upgrades and yields a uniform measure of market reaction.

$$\mathrm{AdjCAR}(0,1)_{i,t,j} = \begin{cases} \text{upgrade}: \sum_{d=0}^{1} \mathrm{ret}_{i,t,j,d} - \sum_{d=0}^{1} \mathrm{ret}_{b,t,j,d} \\ \text{downgrades}: -\left(\sum_{d=0}^{1} \mathrm{ret}_{i,t,j,d} - \sum_{d=0}^{1} \mathrm{ret}_{b,t,j,d} \right) \end{cases}$$

For each firm year I compute the average AdjCAR(0,1) based on all recommendation revisions made for firm *i* during the period *t* as $\text{VRR}_{\text{i,t}} = \frac{1}{n}\sum_{j=1}^{n}\text{AdjCAR}(0,1)_{\text{i,t,j}}$. I examine the cross-sectional variation of VRR_{it} in relation to R&D intensity while controlling for other confounding factors which I discuss in the remainder of this sub-section.[10]

Market risk, firm size and book-to-market: The Sharpe-Lintner capital asset pricing model (CAPM) posits market risk to be a significant explanatory factor of returns. In addition, Fama and French (1993) empirically show size and book-to-market ratio to significantly explain the cross-section of asset returns. To control for the market reaction associated with beta, size and book-to-market I include these variables as controls in the analysis. Consistent with prior evidence, I expect beta (BETA) and book-to-market (BM) to be positively and firm size (LnMV) to be negatively associated with VRR.

Number of business lines the firm operates in: Firms operating in numerous lines of businesses (NSEGS) involve greater business complexity and therefore require greater effort, ability and resources on behalf of analysts. On the other hand business complexity is likely to increase demand for analyst reports which could result in more informative reports.

Earnings value-relevance: Francis, Schipper and Vincent (2002) find that analyst reports are more informative for firms with greater average return volatility on earnings announcement days. Based on these results, they argue that analyst reports and financial

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[10] Table 2.9 describes how each control variable is computed and lists the data sources used.

statements complement each other rather than substitute. I control for return volatility on earnings announcements by including the mean absolute one-day earnings announcement return for the past four quarterly earnings announcements (MAEAR). Based on Francis et al.'s (2002) results I expect a positive coefficient for the MAEAR variable.

Intangible assets and advertising expenditures: Firms' intangible assets and advertising expenditures may create information asymmetry between insiders and outsiders. To the extent firms that heavily invest in R&D projects also have more intangible assets or advertising expenditures we are likely to observe an association between R&D and value of analysts that is not necessarily due to R&D but due to intangible assets and/or brand value. To eliminate this alternative explanation, I control for the level of intangibles (INT) and advertising (ADV) intensities.

Revision direction: Prior literature documents analysts to be overly optimistic and assign high recommendation ratings for investment banking and/or management favoring purposes. Further Hong, Lim and Stein (2000) find that managers highlight good news and delay bad news. To the extent managers delay bad news and analysts avoid disseminating bad information to investors, negative revisions are likely to be more credible to investors. Therefore the relation between the average revision direction (REVDIR) and the value of analysts' recommendations is expected to be negative.

Institutional ownership: Institutional investors rely on analyst research to make investment decisions. Further, analysts are highly concerned about their reputation among fund managers (e.g. Institutional Investor "all-star" rankings). Therefore, institutional ownership (INST) is likely to drive the demand for informative analyst reports and this is likely to result in more informative reports for firms that have strong institutional presence.

Analyst following: The analyst community by allocating more analysts and investing more time and resources to investigate a specific firm can presumably make more valuable recommendations. On the other hand, increased analyst following can diminish opportunities to detect mispricing. To control for the ambiguous effect of analyst following (LnAnalyst) on the value of recommendation revisions I include the natural logarithm of the number of analysts that the firm is being followed by.

Microstructure: Shares that have greater bid-ask spreads or lower prices are likely to appear to be associated with greater returns due to the bid-ask bounce which is not necessarily because of the informativeness of the recommendations but because of security microstructure. To control for the effect of bid-ask on returns I include the trade weighted relative bid-ask spread (TWS) and inverse of price (INVPRC). I expect a positive relation between recommendation revisions' value and the two measures (TWS & INVPRC).

Combining the hypothesis variable, R&D intensity (RND) and control variables discussed above, I employ the following empirical model to examine the relation between the value of analysts' recommendation revisions and R&D expenditures:

$$\begin{aligned}\mathrm{VRR}_{i,t+1} = {} & \alpha + \beta_1 \mathrm{RND}_{it} + \beta_2 \mathrm{BETA}_{it} + \beta_3 \mathrm{BM}_{it} + \beta_4 \mathrm{LnMV}_{it} + \beta_5 \mathrm{NSEGS}_{it} \\ & + \beta_6 \mathrm{MAEAR}_{it} + \beta_7 \mathrm{INT}_{it} + \beta_8\, \mathrm{ADV}_{it} + \beta_9 \mathrm{REVDIR}_{it} + \beta_{10} \mathrm{INST}_{it} \\ & + \beta_{11} \mathrm{LnAnalyst}_{it} + \beta_{12} \mathrm{TWS}_{it} + \beta_{13} \mathrm{INVPRC}_{it} + \varepsilon_{it},\end{aligned}$$

where VRR is the value of recommendation revisions, RND is the ratio of R&D expenditures to sales, BETA is the coefficient of the market return variable in the market model estimated using fiscal year's daily security and market return data, BM is book-to-market ratio at fiscal-year-end, LnMV is natural logarithm of market value at fiscal-year-end, NSEGS is the number of segments the firm is reported to operate in, MAEAR is the average absolute market reaction associated with quarterly earnings announcements during the fiscal year t, INT is the ratio of intangible assets and total assets, ADV is the ratio of advertising expenditures and sales, REVDIR is the percentage of revisions that are upgrades, INST is the institutional ownership percentage, LnAnalyst is the natural logarithm of analyst following, TWS is the trade weighted relative bid-ask spread of the firm based on trades and quotes made during the last month of fiscal-year-end, INVPRC is the inverse of price at fiscal-year-end. Table 2.9 describes in detail how each variable is constructed.

I estimate the regression model using ordinary least squares with Huber-White standard errors clustered by firm. Petersen (2009), using simulations, shows that when residuals are correlated by firm and/or time, random-effects generalized least-squares (GLS with clustered std. errors) estimates are more efficient and standard errors are less biased than OLS, Fama-Macbeth and adjusted Fama-Macbeth estimates. Therefore, for robustness, I re-estimate the empirical model using random-effects GLS estimation with clustered standard errors. Further, for comparability with prior literature I also estimate the model using observation weighted Fama and MacBeth (1973) approach with Newey and West (1987) corrected standard errors. Finally, to control for industry effects, I use

OLS estimation with two-digit SIC industry fixed effects and OLS regression with Fama & French 49 industry fixed effects.

2.6 Sample and Descriptive Statistics

The sample consists of the fiscal years between 1993 and 2004. The sample starts from the year 1993 because the I/B/E/S recommendation file begins in the year 1993 and the sample ends in 2004 because a 2004 fiscal year firm requires return data up to August 30th, 2007.[11] I obtain accounting data from the Compustat fundamental annual file (comp.funda). For each firm-year I collect sales (*sale*), common shares outstanding (*csho*), advertising expense (*xad*), intangible assets (*intan*), R&D expense (*xrd*), book value of common equity (*ceq*) and fiscal year-end closing price (*prcc_f*) data items. I obtain earnings announcement dates (*rdq*) from the Compustat fundamental quarterly file (comp.fundq). To avoid outliers from biasing the results I exclude firms with assets or sales less than or equal to $1 million and firms with share prices less than $1.

Security return data is obtained from Center for Research in Security Prices (CRSP) database. For each firm I collect daily return data (crsp.dsf) adjusted for dividends, stock splits and delisting (using the delisting return provided in CRSP). The CRSP value-weighted, size decile and exchange portfolio daily returns are obtained from CRSP's indice files (crsp.dsi, crsp.erdport3-5). Daily risk-free rates, market returns, Fama

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[11] This is because in Compustat the latest fiscal-year-end-date for a 2004 fiscal year firm is May 31st, 2005. I examine recommendation revisions made during the 12-month period beginning three-months after the fiscal year-end-date (assuming a reporting lag of three-months). Therefore for a May 31st, 2005 fiscal-year-end firm I examine the value of recommendation revisions made during the period September 1st, 2005 – August 31st, 2006. Since I examine returns up to one-year, a recommendation revision made on the last day to be included in the sample, August 31st, 2006 requires return data up to August 30th, 2007.

and French (1993) and Carhart (1997) factors are retreived from Kenneth French through WRDS (ff.factors_daily).

I obtain analyst recommendations from I/B/E/S (ibes.recddet), excluding recommendations issued by anonymous analysts. I identify a recommendation revision as the action of an analyst to change his/her prior recommendation rating. If a recommendation is revised to a more favorable (unfavorable) one I identify it as an upgrade (downgrade). All recommendation reiterations are excluded as they do not signal a change in expectation.

Institutional ownership data is obtained from Thomson Reuters Financial CDA/Spectrum Institutional (13f) Holdings database (tfn.s34). I compute institutional ownership as the ratio of the number of shares held by institutions and the total number of shares outstanding.

Trade and quote data are compiled from the NYSE Trades and Quote (TAQ) database (taq.ct9205-ct0504 and cq9205-cq0504). Based on all intra-day trades and quotes I compute the trade weighted relative bid-ask spread for each firm-year. Due to the computation intensity of this process I only compute the relative bid-ask spread for the last month of each fiscal year.[12]

Table 2.1 provides a summary of the sample selection procedure, the number of observations each filter results in and the industry (Fama & French 49) composition of

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[12] Computing relative bid-ask spread for only one-month per firm-year in the sample required two-weeks of processing in WRDS's supercomputers.

the final sample. The initial sample corresponding to the intersection of CRSP and Compustat files for the fiscal years 1993-2004 consists of 87,587 firm-years. Excluding firms that do not have: (1) ordinary shares (CRSP share codes 10 and 11) traded in one of the major exchanges (NYSE/AMEX/Nasdaq), (2) assets or sales less than or equal to $1 million and (3) share prices less than $1 reduces the sample to 66,667 firm-year observations. The final sample which consists of firm-years with at least one stock recommendation revision from I/B/E/S contains 34,261 firm-year observations that represent 7,537 unique firms. The final sample contains 168,663 recommendation revisions issued by 6,601 financial analysts.

Table 2.2 reports descriptive statistics of the final sample. For each variable, Table 2.2 reports number of non-missing observations, mean, 25th percentile, median, 75th percentile and standard deviation statistics. The mean value of recommendation revisions is 2.6% which suggests that recommendation revisions have a substantial effect on share prices in the direction of the revision. The research and development expenditure (RND) variable has a mean of 5.3% with a standard deviation of 11.4%. The average firm in the final sample has a market capitalization of $589 million ($e^{6.362}$), beta of 0.918, book-to-market ratio of 0.48 and is covered by approximately eight analysts ($e^{2.026}$).

Table 2.3 reports the time-series Pearson product-moment and Spearman's rank correlations among variables. The Pearson (Spearman) correlation between VRR and RND is +0.141 (+0.12) and statistically significant. The positive correlation between RND and VRR is consistent with recommendation revisions being more informative for R&D intensive firms. However, RND is also correlated with market risk (BETA), book-to-market ratio (BM), number of segments and earnings value-relevance (MAEAR) which are also correlated with value of recommendation revisions (VRR). In the cross sectional analysis I control for these variable and other variables reported in Table 2.3.

The correlation matrix in Table 2.3 indicates that there may be multicolinearity issues arising from including all variables simultaneously. There is substantial correlation among the variables firm size (LnMV), institutional ownership (INST), analyst coverage (LnAnalyst), trade-weighted relative bid-ask spread (TWS) and inverse of price (INVPRC). To avoid multicolinearity from biasing standard errors, I check variance inflation factors and avoid specifications where there is significant multicolinearity.

Table 2.4 reports the R&D quintile membership of firms in the ten-year period centered on the year that they were classified into a quintile. The reported statistics in Table 2.4 indicate that firms tend to remain in the same quintile throughout the ten year period. The low variation in quintile membership is more evident among low R&D intensity firms. The mean quintile ranking of firms that were in the first R&D quintile in year *t* ranges between 1.04 and 1.06 for years *t-5* to *t+5*. While firms in other quintiles show a tendency to remain in the same quintile the standard deviation is higher for those quintiles. Further, in untabulated analysis I find the probability of a bottom (top) R&D quintile firm to remain in the same quintile as 98.7% (75.6%). Overall, there is very little transition among the five R&D quintiles and the transition from the bottom quintile to other quintiles is less likely. This suggests that bottom R&D quintile firms are fundamentally different in terms of their R&D investment decisions and that they are not likely to become high R&D firms at any time during the sample period.

2.7 Empirical Results

2.7.1 Univariate Analysis

Table 2.5 reports cumulative average abnormal returns for the event windows: (-1, +1), (-2, +2), (0, +1), (0, +5), (0, +10), and (0, +20) where 0 is the revision day. The first two event windows extend prior to the revision date to take into account possible information leakages and the remaining event windows report returns that begin accumulating on the recommendation revision date.

The univariate analysis suggests a strong market reaction to both upgrades (Panel A) and downgrades (Panel B). The three-day cumulative average abnormal return (CAAR) ranges between 2.38% and 4.68% for upgrades and between -3.35% and -7.07% for downgrades. Further CAARs for all event windows and R&D quintiles are statistically significant at the one-percent significance level. This is consistent with the prior literature on analyst recommendations which documents a strong contemporaneous reaction to recommendation revisions. Provided that recommendation revisions convey substantial information to markets I investigate whether the level of information conveyed by analysts varies between top and bottom R&D quintiles.

In Table 2.5 Panel A, for upgrades, a substantial increase in CAARs for all event windows is evident moving from the first R&D quintile to the top R&D quintile. The CAAR of upgrades for bottom R&D quintile firms is 2.38 percent whereas the CAAR for top R&D quintile firms is 4.68 percent. The 2.3 percent difference between the two CAARs is statistically significant at the one-percent significance level. CAARs for other event windows describe a similar increase in the market reaction associated with upgrades. The CAAR (0, +20) increases from 2.93 percent to 5.25 percent moving from the bottom R&D quintile to the top R&D quintile. The 2.16 percent return difference between top and bottom R&D quintiles is statistically significant.

In Panel B of Table 2.5 I report results for downgrades. During the three-day period centered on the recommendation revision, downgraded firms in the bottom R&D quintile suffer a loss of 3.35 percent whereas firms in the top R&D quintile suffer a much larger loss of 7.07 percent. The 3.57 percent difference between the CAARs for top and bottom R&D quintile firms is statistically different from zero at the one-percent significance level. Results based on alternative event windows describe a similar story; the market reaction associated with analysts' downgrades is substantially greater for top R&D quintile firms than it is for bottom R&D quintile firms.

Overall, univariate analysis results for upgrades and downgrades indicate a significant increase in market reaction moving from bottom to top R&D quintile firms. These results are consistent with financial analysts conveying more information to investors for top R&D quintile firms.

An alternative explanation to the results documented in Table 2.5 is that the mean market reaction to analysts' recommendation revisions for top R&D quintile firms is higher because top R&D quintile firms possess greater market risk, are smaller, have lower book-to-market ratios and are past winners. It may also be that the return differential between top and bottom R&D quintile firms is due to a temporary over-reaction to recommendations of R&D intensive firms. In the calendar-time portfolio regression and cross-sectional analysis I examine to what extent fundamental differences in firm characteristics explain the mean market reaction differential between top and bottom R&D quintile firms.

2.7.2 Calendar Time Portfolio Approach

In this section, I adopt a calendar-time portfolio approach where I estimate the value of recommendation revisions based on returns that extend for a longer period while controlling for market risk, size, book-to-market and momentum effects. By estimating abnormal returns based on a longer period I aim to capture any return drift or reversal that may follow recommendation revisions and provide a long-term assessment of the mispricing analysts detect.

Within each R&D quintile, I construct a hedge portfolio that goes long on upgraded and short on downgraded firms. Revised firms are held for one-year unless the firm is later revised by the analyst who made the initial revision. Since this hedge portfolio takes positions in both upgraded and downgraded firms, it fully captures the value of recommendation revisions. I examine how the abnormal returns associated with the hedge portfolio vary moving from bottom to top R&D quintile firms.

Table 2.6 reports raw and estimated abnormal returns for equal- and value-weighted portfolios. Equal-weighted portfolios equally weight the returns of each firm in the portfolio and therefore provide a more descriptive assessment of the universe of the firms in the sample. However, equally weighting assumes daily rebalancing which may incur substantial transaction costs. In addition because small firms constitute only a small portion of the total market-wide capitalization, equal-weighting may be considered less relevant. Value-weighted portfolios, on the other hand, weight returns based on firm market capitalization and therefore provide an assessment which is more focused on larger firms. Both weighting methods have their advantages and drawbacks. I therefore report both results.

Table 2.6 Panel A reports raw and estimated abnormal returns for equal-weighted portfolios based on the CAPM, three- and four-factor asset pricing models. The hedge portfolio that goes long on upgraded and short on downgraded bottom R&D quintile firms earns a statistically significant 1.226 percent average monthly abnormal return (Jensen's alpha) estimated using the four-factor model. This suggests that analyst recommendation revisions are associated with a monthly average long-term impact of 1.226 which cannot be explained by market, size, book-to-market and momentum factor sensitivities of bottom R&D quintile firms. The average monthly abnormal return associated with recommendation revisions made by analysts for top R&D quintile firms is 1.717 percent. The final row in Table 2.6 Panel A reports the estimation results of a portfolio that captures the difference between the two hedge portfolios (top and bottom R&D quintiles). This portfolio has a 0.491 percent monthly average abnormal return (5.88 percent annualized) which is statistically different from zero at the five-percent significance level. The equal-weighted portfolio return results suggest that controlling for market risk, size, book-to-market and momentum effects, analysts' recommendations are by an annualized 5.88 percent more valuable for top R&D quintile firms than for bottom R&D quintile firms.

The value-weighted portfolio returns are consistent with equal-weighted portfolio return results. The hedge portfolio based on the four-factor model accrues an average monthly abnormal return of 0.607 percent within the bottom R&D quintile firms and

1.117 percent within the top R&D quintile firms. The 0.51 percent monthly average abnormal return difference between top and bottom R&D quintiles' hedge portfolios is statistically significant and corresponds to an annualized return differential of 6.12 percent.

The greater long-term abnormal return associated with recommendation revisions for firms in the top R&D quintile is consistent with analysts providing more informative recommendations to investors and detecting greater levels of mispricing. These results highlight analysts as an important vehicle through which information on the productivity and value of R&D projects gets impounded into market prices.

Finally, it is important to note that the abnormal returns documented in Table 2.6 cannot be arbitraged as they require immediate positioning in revised firms' shares. The results, therefore, are not evidence of a market inefficiency or anomaly. In untabulated analysis I construct portfolios with a delay and find that abnormal returns reported in Table 2.6 disappear when an investor is considered to act upon revisions with a one-day delay.

2.7.3 Cross-Sectional Analysis

The univariate and calendar time portfolio analyses suggest a strong positive relation between R&D intensity and value of analysts' recommendation revisions. In this section I carry out a cross-sectional analysis to test the relation between value of recommendation revisions and R&D intensity while controlling for other confounding factors

Table 2.7 reports the ordinary least-squares estimation results of five specifications of the empirical model. The first specification involves the regression of value of recommendation revisions (VRR) on R&D intensity (RND), book-to-market (BM) and size (LnMV). This specification has the advantage of putting forth the least data requirements but lacks controls for other potential determinants of the value of recommendation revisions. The RND coefficient in this model is estimated to have a coefficient of 0.039 which is statistically significant at the one-percent significance level. Consistent with univariate and calendar-time portfolio analyses the OLS estimation results of the first specification suggest a positive relation between value of analysts' revisions and R&D intensity. Further, the RND coefficient of 0.039 corresponds to an economically significant increase of 17.1% ((0.039*0.114)/0.026) in VRR per RND standard deviation.

In model II I additionally control for the number of segments (NSEGS), earnings value-relevance (MAEAR), intangible assets (INT), advertising expenditures (ADV), percentage of upgrades (REVDIR) and institutional ownership (INST). The coefficient on RND remains to be 0.039 which again suggests a 17.1% increase in analyst informativeness per RND standard deviation. In model III I control for analyst coverage (LnAnalyst) and estimate the coefficient of RND to be 0.035 which indicates a 15.3 percent increase in the value of analysts' recommendations per standard deviation.

In models IV and V I control for potential microstructure issues through the inclusion of trade weighted relative bid-ask spread and share price at fiscal-year-end. The RND coefficients for the two models are 0.036 and 0.032 which are both statistically significant and economically meaningful. The coefficients 0.036 and 0.032 translate to 15.7 and 14 percent increases in analyst informativeness per RND standard deviation.

In Table 2.8, as an alternative to ordinary least-squares estimation, for robustness, I re-estimate model V in Table 2.7 using observation weighted Fama and Macbeth (1973) approach with Newey and West (1987) lag-one corrected standard errors, random-effects GLS estimation, OLS with two-digit SIC fixed effects and OLS with Fama and French 49 industry fixed effects.

Estimation results using alternative methods reported in Table 2.8 are highly consistent with OLS results reported in Table 2.7. The RND coefficient is estimated to be 0.03 and 0.033 when Fama and Macbeth procedure and random-effects GLS estimation methods are used and 0.028 and 0.027 when two-digit SIC and Fama and French 49 industry fixed effect regressions are used, respectively. The lower RND coefficients when controlling for industry is consistent with a part of the positive relation between R&D and value of recommendation revisions being due to industry effects.

The empirical analyses consistently indicate a positive relation between value of recommendation revisions and R&D expenditures. These results imply that financial analysts who are specialized in information acquisition and interpretation activities are able to successfully exploit the greater level of information asymmetry involving R&D intensive firms and make more informative recommendation revisions.

2.7.4 Robustness Checks

Firms with share prices less than $5 or with sales less than $100 million: I replicate the univariate analysis excluding firms with share prices less than $5 or sales less than $100 million. This additional filter significantly reduces the sample size. Nevertheless results remain similar to those derived using the initial sample.

Double sort analysis using R&D intensity and book-to-market ratio: Book-to-market ratio and R&D intensity tend to go hand in hand. The calendar time portfolio approach and the regression analysis control for the book-to-market effect. On the other hand the univariate analysis does not control for the book-to-market effect. To control for the book-to-market ratio in a univariate analysis setting, I modify the approach and carry out a double sorting procedure where I independently sort based on R&D intensity and book-to-market ratio. The return differential between low- and high- R&D intensity firms is evident in both low book-to-market and high book-to-market firms.

2.8 Conclusion

Using a series of univariate, portfolio and cross-sectional tests controlling for risk, business complexity, earnings value-relevance, analyst coverage, institutional ownership and bid-ask spread I find the value of analysts' recommendations to be significantly greater (both statistically and economically) for R&D intensive firms than for low-R&D firms. The empirical results are robust to: (1) alternative estimation methods (Fama & Macbeth (1973), GLS and etc.), (2) industry fixed-effects, and (3) elimination of small companies from the sample.

The results indicate that analysts, despite the challenges they face in R&D intensive firms are able to identify significantly greater amount of mispricing in high R&D firms than low R&D firms. The superior value of recommendations for R&D intensive firms is consistent with analysts undertaking a greater role in the asset price discovery process of R&D intensive firms where there is potentially greater information asymmetry due to the accounting treatment of R&D investments, the nature of R&D firms' businesses and the absence of organized markets for R&D investments. The results also highlight analysts' information acquisition and interpretation activities as an important source of the value of their recommendations. Finally, the results draw attention to financial analysts' recommendations as an important vehicle through which information on the value and productivity of R&D projects gets impounded into security prices.

2.9 Tables for Chapter 2

Table 2.1 Sample Selection and Industry Composition
Panel A overviews the sample selection procedure which resulted in a final sample of 34,261 firm-years (1993-2004), representing 7,537 unique firms. There are 168 recommendation revisions made by 6,601 financial analysts during the sample period. Panel B presents the industry (Fama and French 49) composition of firm-years in the sample.

Panel A: Sample selection procedure	
Total number of firm-years available on CRSP/Compustat merged file for the sample period (fiscal years 1993 through 2004, inclusive)	87,587
Firm-years that have (1) shares traded in NYSE/AMEX/Nasdaq exchanges with share codes 10 or 11, (2) total assets greater than $1 million, (3) sales revenue greater than $1 million and (4) share prices (at fiscal-year-end) greater than $1.	66,667
Final sample: Number of firm-years with at least one recommendation revisions in I/B/E/S data.	34,261
Number of individual firms represented in the final sample.	7,537
Total number of recommendation revisions.	168,663
Number of financial analysts.	6,601

Panel B: Industry Composition

Industry Name	Obs.	Industry Name	Obs.
Agriculture	50	Machinery	1,060
Aircraft	124	Measuring and Control Equipment	562
Apparel	297	Medical Equipment	895
Automobiles and Trucks	434	Non-Metallic and Industrial Metal Mining	117
Banking	2,526	Other	285
Beer & Liquor	95	Personal Services	378
Business Services	1,913	Petroleum and Natural Gas	1,336
Business Supplies	388	Pharmaceutical Products	1,350
Candy & Soda	95	Precious Metals	74
Chemicals	563	Printing and Publishing	381
Coal	39	Real Estate	118
Communication	1,034	Recreation	184
Computer Software	2,690	Restaurants, Hotels, Motels	767
Computers	969	Retail	1,966
Construction	375	Rubber and Plastic Products	190
Construction Materials	585	Shipping Containers	122
Consumer Goods	543	Ships	65
Defense	65	Steel Works Etc.	535
Electrical Equipment	910	Textiles	169

Panel B - continued

Industry Name	Obs.	Industry Name	Obs.
Electronic Equipment	1,829	Tobacco Products	42
Entertainment	389	Trading	1,893
Fabricated Products	94	Transportation	875
Food Products	423	Utilities	1,195
Healthcare	796	Wholesale	1,339
Insurance	1,137		

Table 2.2 Descriptive Statistics

This table provides descriptive statistics of the final sample which consists of 34,261 firm-years for the fiscal years 1993-2004. For each variable, the table reports the number of non-missing observations, mean, 1st quartile, median, 3rd quartile and standard deviation. VRR is the value of recommendation revisions, RND is R&D intensity, BETA is the market risk of the firm measured as the coefficient on the market return of the CAPM model, BM is book-to-market ratio, LnMV is the natural logarithm of market value, NSEGS is the number of segments the firm operates in, MAEAR is the mean absolute earnings announcement return of earnings announcements, INT is intangible asset intensity, ADV is advertising intensity, REVDIR is the percentage of upgrades out of all revisions, INST is the institutional ownership percentage, LnAnalyst is the natural logarithm of analyst coverage, TWS is trade-weighted relative bid-ask spread, and INVPRC is the inverse of price. Appendix A provides detailed descriptions and formulas of each variable. All variables are winsorized at the top and bottom five-percentile.

Variable	Obs.	Mean	Q1	Median	Q3	Std. Dev
VRR	34,261	0.027	0.000	0.016	0.043	0.044
RND	34,261	0.053	0.000	0.000	0.050	0.114
BETA	33,112	0.918	0.491	0.818	1.249	0.573
BM	34,257	0.480	0.249	0.424	0.646	0.303
LnMV	34,261	6.362	5.133	6.247	7.458	1.570
NSEGS	30,089	1.901	1.000	1.000	3.000	1.326
MAEAR	33,763	0.032	0.016	0.026	0.043	0.021
INT	34,261	0.092	0.000	0.017	0.140	0.137
ADV	34,261	0.007	0.000	0.000	0.006	0.015
REVDIR	34,261	0.421	0.125	0.429	0.611	0.326
INST	33,997	0.506	0.298	0.515	0.708	0.247
LnAnalyst	34,261	2.026	1.386	2.079	2.639	0.769
TWS	31,414	0.018	0.008	0.014	0.024	0.013
INVPRC	34,261	0.071	0.030	0.049	0.087	0.062

Table 2.3 Correlation Matrix

This table reports time-series correlations among all variables. Correlations reported on the top-triangle are Pearson product-moment correlations and those reported on the bottom-triangle are Spearman's rank correlations. The reported correlations are based on the final sample which consists of 34,261 firm-years for the fiscal years 1993-2004. All variables are winsorized at the top and bottom five-percentile

	VRR	RND	BETA	BM	LnMV	NSEGS	MAEAR	INT	ADV	REVDIR	INST	LnAnalyst	TWS	INVPRC
VRR	1	0.141	0.152	-0.070	-0.113	-0.113	0.133	0.027	0.025	-0.039	-0.010	-0.083	0.033	0.098
RND	0.120	1	0.377	-0.235	-0.130	-0.230	0.214	-0.101	0.004	-0.022	-0.087	-0.066	0.007	0.198
BETA	0.149	0.348	1	-0.236	0.194	-0.130	0.254	-0.015	0.050	-0.006	0.187	0.260	-0.230	-0.009
BM	-0.085	-0.299	-0.255	1	-0.299	0.113	-0.049	-0.032	-0.088	0.016	-0.086	-0.127	0.260	0.303
LnMV	-0.063	-0.059	0.220	-0.285	1	0.326	-0.263	0.070	0.043	0.084	0.453	0.743	-0.595	-0.638
NSEGS	-0.096	-0.149	-0.119	0.145	0.299	1	-0.195	0.091	-0.063	0.055	0.139	0.193	-0.130	-0.204
MAEAR	0.126	0.237	0.260	-0.093	-0.263	-0.205	1	0.024	0.053	-0.037	-0.084	-0.141	0.192	0.309
INT	0.026	-0.027	-0.001	-0.015	0.099	0.148	0.016	1	0.043	-0.018	0.126	0.037	0.006	0.002
ADV	0.019	-0.016	0.036	-0.064	0.001	-0.095	0.039	0.002	1	-0.020	-0.031	0.054	-0.029	0.008
REVDIR	-0.021	-0.008	0.008	0.005	0.116	0.062	-0.039	-0.010	-0.019	1	0.059	0.090	-0.029	-0.030
INST	0.032	-0.002	0.210	-0.080	0.466	0.135	-0.058	0.152	-0.058	0.075	1	0.483	-0.360	-0.415
LnAnalyst	-0.039	-0.023	0.274	-0.114	0.744	0.179	-0.131	0.066	0.029	0.127	0.478	1	-0.495	-0.396
TWS	0.003	-0.057	-0.245	0.249	-0.647	-0.132	0.187	-0.010	-0.034	-0.058	-0.360	-0.535	1	0.614
INVPRC	0.076	0.104	-0.030	0.307	-0.739	-0.233	0.307	-0.025	0.004	-0.075	-0.419	-0.464	0.633	1

Table 2.4 R&D Quintile Membership across Time

This table reports the mean R&D quintile of sample firms during the ten-year period centered on the portfolio formation year. The first column indicates R&D quintiles. Quintile 1 is composed of firms with the least R&D intensity and quintile 5 is composed of firms with greatest R&D intensity. The remaining 10 columns report the mean R&D quintile for the years relative to portfolio formation date. In parentheses are the standard deviations of quintile assignments.

	Fiscal Year Relative to Portfolio Formation									
R&D Intensity	-5	-4	-3	-2	-1	1	2	3	4	5
1 (Low R&D)	1.06	1.05	1.05	1.04	1.02	1.02	1.03	1.04	1.04	1.04
	(0.34)	(0.32)	(0.3)	(0.26)	(0.21)	(0.2)	(0.24)	(0.26)	(0.28)	(0.29)
2	2.26	2.22	2.17	2.12	2.08	2.01	1.98	1.97	1.93	1.88
	(0.83)	(0.81)	(0.75)	(0.69)	(0.57)	(0.53)	(0.62)	(0.66)	(0.68)	(0.7)
3	3.32	3.25	3.23	3.18	3.10	2.99	2.95	2.90	2.84	2.75
	(0.94)	(0.9)	(0.86)	(0.78)	(0.66)	(0.64)	(0.77)	(0.82)	(0.86)	(0.87)
4	4.05	4.02	4.00	4.01	4.00	3.90	3.81	3.76	3.68	3.60
	(0.89)	(0.87)	(0.82)	(0.76)	(0.64)	(0.66)	(0.75)	(0.8)	(0.85)	(0.86)
5 (High R&D)	4.54	4.57	4.61	4.66	4.76	4.70	4.52	4.39	4.29	4.21
	(0.84)	(0.79)	(0.76)	(0.71)	(0.6)	(0.64)	(0.79)	(0.89)	(0.92)	(0.95)

Table 2.5 Univariate Analysis

This table reports the cumulative average abnormal returns associated with analysts' revisions. Panel A and B report result for upgrades and downgrades, respectively. The first column reports the R&D quintile and the remaining columns list the CAARs for the event windows: (-1, +1), (-2, +2), (0, +1), (0, +5), (0, +10) and (0, +20). To compute abnormal returns each upgraded/downgraded firm is matched to a market and size decile using the CRSP-reported exchange and decile number as of the revision date and the difference between the revised firm's raw return and the matched size-exchange portfolio's return is used as the abnormal return. To compute standard errors taking into account cross-correlations I compute quarterly CAARs for each R&D quintile and using the Fama and Macbeth (1973) procedure with Newey and West (1987) corrected standard errors. * denotes significance at a five-percent significance level and ** denotes significance at a one-percent significance level

R&D Intensity Category	CAAR (-1, +1)	CAAR (-2, +2)	CAAR (0, +1)	CAAR (0, +5)	CAAR (0, +10)	CAAR (0, +20)
Panel A: Upgrades						
1 (Low R&D)	2.38%**	2.53%**	1.92%**	2.29%**	2.60%**	2.93%**
	(7.27)	(6.96)	(6.36)	(5.9)	(5.55)	(4.74)
2	2.30%**	2.46%**	1.92%**	2.22%**	2.55%**	2.84%**
	(6.93)	(7.08)	(5.18)	(4.66)	(5.22)	(4.13)
3	3.22%**	3.35%**	2.71%**	3.13%**	3.56%**	4.22%**
	(5.7)	(5.57)	(5.35)	(5.85)	(5.7)	(6.31)
4	4.13%**	4.53%**	3.22%**	3.66%**	4.02%**	4.83%**
	(5.44)	(6.22)	(4.55)	(4.43)	(4.39)	(4.96)
5 (High R&D)	4.68%**	4.97%**	3.61%**	4.03%**	4.46%**	5.25%**
	(7.33)	(6.95)	(7.29)	(7.41)	(7.48)	(5.78)
5-1	2.30%**	2.40%**	1.63%**	1.66%**	1.74%**	2.16%**
	(5.69)	(5.54)	(5.51)	(6.35)	(4.15)	(2.88)
Panel B: Downgrades						
1 (Low R&D)	-3.35%**	-3.73%**	-2.54%**	-2.91%**	-3.04%**	-3.11%**
	(-5.21)	(-5.82)	(-5.27)	(-5.45)	(-5.62)	(-5.49)
2	-3.63%**	-3.94%**	-2.76%**	-3.12%**	-3.35%**	-3.45%**
	(-5.16)	(-5.33)	(-5.29)	(-5.07)	(-4.62)	(-5.42)
3	-4.81%**	-4.99%**	-3.77%**	-3.97%**	-3.61%**	-3.43%**
	(-4.91)	(-5.1)	(-4.79)	(-5.36)	(-4.31)	(-4.62)
4	-5.84%**	-6.02%**	-4.58%**	-4.57%**	-4.43%**	-4.00%**
	(-5.14)	(-5.26)	(-5.02)	(-4.74)	(-4.34)	(-4.25)
5 (High R&D)	-7.07%**	-7.43%**	-5.63%**	-5.87%**	-5.75%**	-5.70%**
	(-5.67)	(-5.63)	(-5.69)	(-5.64)	(-6.37)	(-5.79)
5-1	-3.57%**	-3.65%**	-2.98%**	-2.89%**	-2.66%**	-2.52%**
	(-5.01)	(-4.64)	(-5.11)	(-4.61)	(-4.61)	(-3.25)

Table 2.6 Monthly Returns Earned by Analyst Revision Portfolios

This table presents percentage monthly returns earned by portfolios formed according to analyst recommendation revisions. Raw returns are the mean percentage monthly returns earned by each portfolio. The CAPM intercept is the estimated intercept (Jensen's alpha) from a time-series regression of the portfolio returns on the market excess return. The intercept for the three-factor model is the estimated intercept from a time-series regression of portfolio returns on market excess returns, a zero-investment size portfolio's (SMB), and a zero-investment book-to-market portfolio's (HML) returns. The four-factor model is the estimated intercept from a time-series regression of portfolio returns on excess market returns, size (SMB), book-to-market (HML) and momentum (UMD) portfolio returns. Panel A and B report results for the equal- and value-weighted portfolios, respectively. In parentheses are *t*-statistics which are based on Newey and West (1987) (12-month lag) corrected standard errors. * denotes returns significance at a level of five-percent and ** denotes returns that are significant at the one-percent significance level.

Panel A: Equal-Weighted Portfolio Returns

	Raw			CAPM			Three-Factor			Four-Factor		
	Short	Long	Hedge	Short	Long	Hedge	Short	Long	Hedge	Short	Long	Hedge
1	0.367	1.716**	1.349**	-0.484	0.869**	1.353**	-0.830**	0.494**	1.324**	-0.638**	0.588**	1.226**
	(1.02)	(6.19)	(10.6)	(-1.79)	(3.45)	(10.6)	(-4.85)	(3.95)	(9.5)	(-5.82)	(4.87)	(10.88)
2	0.468	1.710**	1.241**	-0.429	0.809**	1.238**	-0.705**	0.501**	1.206**	-0.418**	0.680**	1.098**
	(1.31)	(5.52)	(8.51)	(-1.92)	(3.53)	(8.27)	(-3.99)	(3.48)	(9.96)	(-2.58)	(4.47)	(9.84)
3	0.675	2.195**	1.520**	-0.441	1.047**	1.489**	-0.355	1.206**	1.561**	0.059	1.464**	1.406**
	(1.2)	(4.24)	(12.74)	(-1.47)	(3.36)	(11.61)	(-1.55)	(4.75)	(11.35)	(0.21)	(4.97)	(10.58)
4	0.904	2.560**	1.657**	-0.394	1.252*	1.646**	-0.058	1.666**	1.723**	0.379	1.917**	1.537**
	(1.2)	(3.37)	(6.76)	(-0.84)	(2.23)	(6.65)	(-0.17)	(4.17)	(6.42)	(1.08)	(4.33)	(6.89)
5	0.439	2.331*	1.893**	-0.871	0.928	1.799**	-0.529	1.403**	1.932**	-0.119	1.598**	1.717**
	(0.42)	(2.3)	(7.86)	(-1.15)	(1.28)	(7.29)	(-1.17)	(2.93)	(7.76)	(-0.24)	(3.21)	(7.72)
Hedge	0.072	0.615	0.544**	-0.387	0.059	0.446*	0.301	0.909	0.608**	0.518	1.009*	0.491*
	(0.08)	(0.65)	(2.74)	(-0.44)	(0.07)	(2.27)	(0.56)	(1.72)	(2.87)	(0.95)	(2.04)	(2.32)

Panel B: Value-Weighted Portfolio Returns

	Raw			CAPM			Three-Factor			Four-Factor		
	Short	Long	Hedge	Short	Long	Hedge	Short	Long	Hedge	Short	Long	Hedge
1	0.562	1.187**	0.625**	-0.277	0.338*	0.615**	-0.493**	0.131	0.623**	-0.460**	0.147*	0.607**
	(1.74)	(4.29)	(7.05)	(-1.54)	(2.55)	(7.26)	(-4.62)	(1.84)	(7.59)	(-5.22)	(2.29)	(7.73)
2	0.440	1.200**	0.760**	-0.433	0.311	0.744**	-0.497	0.227	0.724**	-0.273	0.365*	0.638**
	(1.03)	(3.2)	(3.49)	(-1.67)	(1.5)	(3.53)	(-1.64)	(1.15)	(3.36)	(-1.17)	(2.18)	(3.28)
3	0.336	1.350*	1.013**	-0.692**	0.316	1.008**	-0.298	0.705**	1.002**	-0.092	0.780**	0.871**
	(0.59)	(2.54)	(6.31)	(-2.63)	(1.19)	(6.12)	(-1.88)	(3.64)	(6.49)	(-0.64)	(4.05)	(6.64)
4	1.034	1.739**	0.705**	-0.075	0.669*	0.743**	0.379	1.086**	0.708**	0.480*	1.035**	0.555**
	(1.74)	(2.97)	(4.21)	(-0.27)	(2.08)	(4.5)	(1.6)	(3.94)	(3.78)	(2.07)	(4.12)	(3.8)
5	-0.336	0.914	1.250**	-1.686*	-0.478	1.208**	-1.038	0.267	1.305**	-0.676	0.441	1.117**
	(-0.3)	(0.84)	(5.27)	(-2.14)	(-0.64)	(4.7)	(-1.74)	(0.54)	(5.38)	(-1.22)	(0.93)	(5.7)
Hedge	-0.898	-0.273	0.624*	-1.409	-0.816	0.593*	-0.546	0.136	0.682**	-0.216	0.294	0.510*
	(-0.88)	(-0.28)	(2.57)	(-1.52)	(-0.95)	(2.32)	(-0.83)	(0.25)	(2.91)	(-0.36)	(0.6)	(2.5)

Table 2.7 Cross-Sectional Analysis

This table reports the ordinary least-squares estimation results with clustered standard errors by firm (Huber-White) of five specifications of the empirical model:

$$VRR_{i,t+1} = \alpha + \beta_1 RND_{it} + \beta_2 BETA_{it} + \beta_3 BM_{it} + \beta_4 LnMV_{it} + \beta_5 NSEGS_{it} + \beta_6 MAEAR_{it} + \beta_7 INT_{it} + \beta_8 ADV_{it} + \beta_9 REVDIR_{it} + \beta_{10} INST_{it} + \beta_{11} LnAnalyst_{it} + \beta_{12} TWS_{it} + \beta_{13} INVPRC_{it} + \varepsilon_{it}.$$

The reported *t*-statistics are based on Huber-White standard errors clustered by firm. The final three rows report the number of observations, F-value, R-square and adjusted R-square for each model. * denotes significance at the five-percent significance level and ** denotes significance at the one-percent significance level.

	I Model	II Model	III Model	IV Model	V Model
RND	0.039**	0.039**	0.035**	0.036**	0.032**
	(11.25)	(10.90)	(9.96)	(9.96)	(8.83)
BETA	0.009**	0.005**	0.007**	0.005**	0.006**
	(16.75)	(8.32)	(11.63)	(8.94)	(11.14)
BM	-0.007**	-0.002	-0.003**	-0.002*	-0.007**
	(-6.24)	(-1.60)	(-2.70)	(-1.99)	(-5.78)
LnMV	-0.002**				-0.002**
	(-14.67)				(-6.77)
NSEGS		-0.001**	-0.000	-0.001**	0.000
		(-3.81)	(-1.28)	(-4.08)	(0.73)
MAEAR		0.218**	0.190**	0.220**	0.168**
		(14.91)	(12.86)	(14.25)	(11.10)
INT		0.017**	0.018**	0.016**	0.018**
		(7.45)	(8.11)	(7.24)	(8.32)
ADV		0.061**	0.071**	0.058**	0.063**
		(2.90)	(3.47)	(2.68)	(3.07)
REVDIR		-0.004**	-0.003**	-0.005**	-0.004**
		(-4.78)	(-3.84)	(-4.98)	(-4.08)
INST		0.004**			
		(3.11)			
LnAnalyst			-0.004**		
			(-10.69)		
TWS				0.030	
				(1.31)	
INVPRC					0.025**
					(3.82)
Constant	0.035**	0.014**	0.023**	0.016**	0.025**
	(23.84)	(11.28)	(17.41)	(13.84)	(12.82)
N	33,108	28,782	28,891	26,719	28,891
F-Value	235.938**	102.006**	117.962**	98.820**	109.852**
R^2	0.042	0.044	0.048	0.045	0.048
Adj. R^2	0.041	0.044	0.047	0.045	0.048

Table 2.8 Cross-Sectional Analysis - Alternative Estimation Methods

This table reports the Fama and Macbeth (1973), random-effects GLS, and industry-fixed effects estimation results of the empirical model:

$$VRR_{i,t+1} = \alpha + \beta_1 RND_{it} + \beta_2 BETA_{it} + \beta_3 BM_{it} + \beta_4 LnMV_{it} + \beta_5 NSEGS_{it} + \beta_6 MAEAR_{it} + \beta_7 INT_{it} + \beta_8 ADV_{it} + \beta_9 REVDIR_{it} + \beta_{13} INVPRC_{it} + \varepsilon_{it}.$$

The *t*-statistics for the Fama and Macbeth regression are based on Newey and West (1987) corrected standard errors. The *t*-statistics reported for the remaining three estimation methods are based on Huber White standard errors clustered by firm. The final three rows report the number of observations, F-value, R-square and adjusted R-square for each model. * denotes significance at the five-percent significance level and ** denotes significance at the one-percent significance level.

	Fama Macbeth (Newey West Corrected)	Random Effects GLS (clustered standard errors)	Industry Fixed Effects (Two-Digit SIC)	Industry Fixed Effects (Fama French 49)
RND	0.030**	0.033**	0.028**	0.027**
	(6.15)	(8.23)	(7.12)	(6.48)
BETA	0.009**	0.004**	0.004**	0.004**
	(5.45)	(5.76)	(7.28)	(7.10)
BM	-0.007**	-0.007**	-0.005**	-0.005**
	(-12.25)	(-5.11)	(-4.29)	(-4.58)
LnMV	-0.004**	0.001**	-0.001**	-0.001**
	(-5.42)	(2.66)	(-3.93)	(-4.24)
NSEGS	-0.001**	0.001*	0.000*	0.001*
	(-3.12)	(2.32)	(2.16)	(2.42)
MAEAR	0.056**	0.116**	0.140**	0.140**
	(3.89)	(7.37)	(9.19)	(9.16)
INT	0.007*	0.019**	0.014**	0.015**
	(2.97)	(7.34)	(6.09)	(6.23)
ADV	0.041*	0.046	0.039	0.040
	(2.25)	(1.87)	(1.79)	(1.81)
REVDIR	-0.003*	-0.003**	-0.004**	-0.004**
	(-2.43)	(-3.89)	(-4.08)	(-4.00)
INVPRC	-0.010*	0.031**	0.026**	0.026**
	(-2.22)	(4.16)	(3.92)	(3.84)
Constant	0.017**	0.013**	0.023**	0.024**
	(3.44)	(5.97)	(11.60)	(11.93)
N	28,891	28,891	28,891	28,891
F-Value	26.876**	495.82** (Wald)	45.277**	41.902**
R2	0.056	0.040	0.060	0.058
Adj. R2	0.054	-	0.057	0.056

Table 2.9 Variable Descriptions
This table lists and describes the variables used in this study. For each variable the source of data and the file locations under WRDS's directory system is indicated in parentheses.

Label	Description
VRR	The two-day mean market reaction (conditional on revision) associated with revisions for each firm-year. $\text{VRR}_{\text{i,t}}$ is $\frac{1}{n}\sum_{j=1}^{n}\text{AdjCAR}(0,1)_{\text{i,t,j}}$ where AdjCAR(0,1) equals $\sum_{\text{d=0}}^{1}\text{ret}_{\text{i,t,j,d}} - \sum_{\text{d=0}}^{1}\text{ret}_{\text{b,t,j,d}}$ for upgrades and $-\left(\sum_{\text{d=0}}^{1}\text{ret}_{\text{i,t,j,d}} - \sum_{\text{d=0}}^{1}\text{ret}_{\text{b,t,j,d}}\right)$ for downgrades. $\text{Ret}_{\text{i,t,j,d}}$ is the raw return of firm *i*'s shares on day *d* retrieved from the CRSP daily file (`crsp.dsf`) adjusted for delisting returns. $\text{Ret}_{\text{b,t,j,d}}$ is the size and exchange index return compiled from CRSP index files (`crsp.erdport3-erdport5`)
RND	Annual research and development expenditure scaled by annual sales (xrd/sale). Compustat fundamental annual file(`comp.funda`).
BETA	Coefficient on the market model ($ret_{i,t,d} = \alpha_{i,t} + \beta_{i,t}Mkt + \varepsilon_{i,t,d}$) estimated using daily security and market data. Security and market return are obtained from CRSP daily (`crsp.dsf`) and index files (`crsp.dsi`), respectively.
BM	The ratio of common equity and market value at fiscal year-end (ceq/(prcc_f*csho)) computed using data from the Compustat fundamental annual file (`comp.funda`).
LnMV	Natural logarithm of the market value at fiscal-year-end computed as ln(prcc_f*csho) using data from the Compustat fundamental annual file (`comp.funda`).
NSEGS	Number of segments that the firm operates in. Compustat Segment Files (`comp.segitem`).
MAEAR	Mean absolute market-adjusted one-day earnings announcement return during the past four quarterly earnings announcements CRSP Daily File (`crsp.dsf`). Earnings announcement dates (rdq) are obtained from the Compustat fundamental quarterly file (`comp.fundq`).
INT	Ratio of intangible assets and total assets (intan/at). Compustat fundamental annual file(`comp.funda`).
ADV	Ratio of advertising expenditures and sales (xad/sale). Compustat fundamental annual file(`comp.funda`).
REVDIR	Percentage of upward recommendation revisions. I/B/E/S Recommendation File (`ibes.recddet`).
INST	Institutional ownership percentage computed as the ratio of number of shares held by institutions and total shares outstanding. Thomson Reuters Financial CDA/Spectrum Institutional (13f) Holdings data (`tfn.s34`).

LnAnalyst	Natural logarithm of analyst coverage obtained from I/B/E/S Recommendation File (`ibes.recddet`).
TWS	Trade weighted relative bid-ask spread based on trades made during the last month of the fiscal year. NYSE Trade and Quote Database (`taq.ct9205-ct0504 and taq. cq9205-cq0504`).
INVPRC	Inverse of price at fiscal-year-end (1/prcc_f) compiled from the Compustat fundamental annual file (`comp.funda`).

Chapter 3 Analysts' Recommendation Revisions and Subsequent Earnings Surprises: Pre- and Post- Regulation FD

3.1 Introduction

Earnings-related selective disclosure was one of the most publicized cases of unfair disclosure that contributed to Regulation Fair Disclosure's acceptance. A significant number of comment letters expressed frustration on the basis of the belief that corporations were giving private earnings guidance to select analysts and investors. Prior to Regulation FD, advance warnings of earnings results or pre-disclosure of other material information to certain "selected" analysts or institutional investors were common. Inevitably, such disclosure policies helped certain *selected* investors earn profits or avoid losses at the expense of *unselected* investors. In response, the Securities and Exchange Commission (SEC) passed Regulation FD and listed earnings-related disclosure on top of the list of potential material information that need to be disclosed simultaneously to all market participants.[1]

SEC viewed earnings-related selective disclosure as a strong threat against the integrity of capital markets and took action to prevent it. Hence, it is important to investigate whether SEC's action was effective in reducing earnings-related selective disclosure. To assess the effectiveness of Regulation FD in hampering earnings-related selective disclosure, this essay compares analysts' superior knowledge of upcoming earnings results in the pre- and post- Regulation FD periods.

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[1] Selective Disclosure and Insider Trading, Release No. 33-7881, August 15, 2000.

Superior knowledge of upcoming earnings results is measured using the association between analysts' recommendation revisions made during the pre-earnings-announcement period and subsequent earnings surprises. Analysts' recommendations as opposed to their earnings forecasts are used because while both selective and public disclosures are likely to affect analysts' earnings forecasts, selective disclosure is more likely to lead to a change in analysts' recommendation ratings.[2]

The empirical results reveal that prior to Regulation Fair Disclosure's acceptance, recently upgraded firms exhibited earnings announcement returns that were on average 1.22 percent higher than recently downgraded firms. On the other hand, the return differential between upgraded and downgraded firms declined to 0.7 percent after Regulation FD took effect.[3] Additionally, regression analysis controlling for the post-earnings-announcement drift, return momentum, accruals anomaly and institutional trading indicates a significant decline in the association between revisions and subsequent earnings surprises after Regulation FD took effect.[4]

The existence of a relation between the change in analysts' recommendations and subsequent earnings-announcement returns represents indirect evidence that some form of information acquisition either through selective disclosure or analysts' own research

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[2] In the case of a public disclosure, prices are expected to quickly adjust to new information and leave no reward for a new recommendation. Under such circumstances analysts are not expected to revise their recommendations. On the other hand in the case of selective corporate disclosure, due to the private nature of the disclosure, prices are unlikely to fully reflect the disclosure and recommendations may be more feasible.

[3] Inferences derived from alternative earnings surprise measures based on analyst expectations and time-series models are qualitatively similar.

[4] I control for these factors because it may be that analysts revise their recommendations in response to these predictive variables rather than to selective disclosure or their information acquisition activities.

was taking place. Under the assumption that average analyst effort remained stable across the pre- and post- Regulation FD periods, the change in analysts' superior earnings-related information is attributable to the change in selective disclosure. Therefore the decline in the association between recommendation revisions and earnings surprises supports the view that earnings-related selective disclosure declined in the aftermath of Regulation FD.

Further, I test whether the market reaction associated with analysts' recommendations in the pre-earnings-announcement period relative to non-earnings periods declined in the post-Regulation FD period. Ivković and Jegadeesh (2004) find the market reaction associated with analysts' earnings forecasts and recommendation revisions to increase as the earnings announcement date approaches (particularly during the last week before the earnings announcement). They attribute the greater level of market impact generated by analysts' forecasts and recommendations to analysts' independent information collection and early access to inside information. If Regulation FD had a negative impact on analysts' earnings-related private information, the difference between the mean market impact associated with analysts' recommendation revisions in the pre-earnings-announcement period and non-earnings-announcement periods should be lower in the post-Regulation FD period. Consistently, the results suggest that in the post- Regulation FD period the market reaction differential associated with recommendation revisions between the pre-earnings and non-earnings periods was significantly lower than the average differential in the Pre-Regulation FD period.

Finally, I test the performance of a trading strategy designed to exploit analysts' earnings-related superior knowledge. The designed trading strategy is found – in the pre-

Regulation FD period – to accrue a significantly positive average monthly return of 4.6 percent (before transaction costs) after controlling for market risk, size, book-to-market and momentum effects. In the post-Regulation FD period, the trading strategy does not provide significantly positive abnormal returns. Overall, this paper's results are consistent with Regulation FD having reduced the practice of selective earnings-related disclosure.

This paper contributes to the extant literature by providing evidence on analysts' earnings related superior information before and after Regulation FD. Regulation FD was preceded by intense objection that the rule would harm the level of corporate disclosure. Consequently, prior studies on Regulation FD focused on whether the rule damaged corporate disclosure level, increased earnings volatility, or reduced forecast accuracy. Although somewhat mixed, the majority of the prior literature suggests that Regulation FD did not have significant adverse effects on corporate disclosure. Given prior evidence, this paper assesses Regulation FD's impact on analysts' superior earnings-related information.

3.2 Literature Review and Hypotheses Development

In response to growing concerns of select individuals getting access to inside information, the SEC passed Regulation FD which was concerned with the fair disclosure of nonpublic material information. Regulation FD required managers to disseminate any material information simultaneously to all market participants and prohibited selective disclosure. However, many securities markets professionals argued that bringing additional restrictions on corporate disclosure would reduce the quantity and quality of information available to capital markets. Analysts defended that reduced disclosure would cause less accurate earnings expectations and greater return volatility when firms announce earnings. After Regulation FD took effect there was increased concern whether the rule reduced firms' aggregate disclosure and adversely affected the value of analysts' forecasts and recommendations.

In response to concerns of Regulation FD harming corporate disclosure, Heflin, Subramanyam and Zhang (2003) examined the informational efficiency of stock prices during the pre-earnings-announcement period, the accuracy and dispersion of analysts' earnings forecasts and firms' voluntary disclosure frequency before and after Regulation FD. Contrary to Regulation FD's critics, Heflin et al. found no evidence of a reduction in disclosure or earnings forecast accuracy. On the contrary their evidence suggested some improvement. They found the efficiency of stock prices to be higher and documented that the frequency in which firms voluntarily disclose forward-looking earnings-related information increased. Similarly, Bailey, Li, Mao and Zhong (2003) found no significant change in return volatility around earnings announcements, but a sharp increase in trading volume and increase in forecast dispersion. Further, they found that corporations increased the quantity of voluntary disclosure. They concluded that Regulation FD increased the quantity of information available to the public.

Lee, Lee, Rosenthal and Gleason (2004) extended Heflin et al. and Bailey et al.'s analysis by investigating whether volatility during earnings announcements increased in the post-Regulation FD period. Similar to Heflin et al.'s findings, Lee, Rosenthal and Gleason found no adverse effect of Regulation FD on earnings announcement return volatility. In addition, Chiyachantana, Jiang, Taechapiroontong and Wood (2004) documented that Regulation FD was effective in improving liquidity and decreasing information asymmetry. Further, Bushee, Matsumoto and Miller (2003) reported no adverse effect of Regulation FD on the total amount of information disclosed during conference calls. Similarly Charoenrook and Lewis (2005) found that the same amount of firm-specific information is reflected in stock prices before and after Regulation FD. Their evidence indicated that Regulation FD did not have any adverse effect. They also documented that firms increasingly used earnings guidance to substitute for selective disclosure.

The early work on Regulation FD comparing the pre- and post- Regulation FD periods received criticism of potential common market wide factors blurring the results. Accordingly, Francis, Nanda and Wang (2006) using an innovative approach that relied on foreign firms listed in U.S. markets as control firms, provided empirical results invulnerable to common market wide factors. Foreign firms are exempt from the requirement of Regulation FD, thus analysts may obtain private earnings guidance from ADR firms. As expected, Francis, Nanda and Wang (2006) found that the value of analysts' reports for U.S. firms declined relative to ADR firms. Their results are consistent with Regulation FD having reduced private information flows to analysts.

In a similar spirit, Jorion, Liu and Shi (2005) exploited credit rating agencies exemption from Regulation FD to analyze the impact of Regulation FD. Jorion et al. (2005) found that the informational value of rating agencies' credit rating changes increased after Regulation FD took effect. They concluded that credit rating agencies achieved an informational advantage amid Regulation FD. Irani (2004) investigated the impact of conference calls in the pre- and post- Regulation FD periods. He found that conference calls in the post-Regulation FD period improved analyst forecast accuracy significantly higher than in the pre-Regulation FD period. Based on these findings he concluded that more earnings-related information was being released during conference calls in the post-FD period. Eleswarapu, Thompson and Venkataraman (2004) found trading costs at earnings announcements to have declined particularly for smaller and less liquid stocks. They also found evidence suggesting return volatility to be lower. Their results support the view that the SEC diminished informed investors' advantage.

Finance theory stipulates the market reaction associated with analysts' recommendation and earnings forecast revisions to be a function of analysts' private information. This lends a testable hypothesis to assess the impact of Regulation FD. Based on this approach Gintschel and Stanimir (2004) studied the value of analysts' information outputs. Using analysts' recommendations and earnings forecasts they found the absolute price impact of financial analysts' forecasts and recommendations to have declined by 28 percent. They concluded that Regulation FD curtailed selective disclosure. Cornett, Tehranian and Yalcin (2007) extended Gintschel and Stanimir (2004) investigation by evaluating the impact on affiliated and unaffiliated analysts. They found that the market reaction to affiliated analysts' recommendation changes decreased significantly after the passage of Regulation FD. The lower value of analysts' recommendation revisions is consistent with Regulation FD having reduced selective disclosure hence analysts' private information resulting in lower impact of recommendations.

On the other hand, Irani and Karamanou (2003) found a decrease in analyst following and increase in forecast dispersion. Using a much larger sample, Agrawal, Chadha and Chen (2006) found an increase in forecast dispersion and reduction in forecast accuracy particularly for early forecasts and for smaller companies. Ahmed and

Schneible (2007) found that the volume-return relation significantly declined in the post-FD period suggesting that differences in information quality across investors diminished after Regulation FD took effect. Nevertheless, they found the reduction to be driven by small and high-tech firms. Ahmed et al. (2007) concluded that FD succeeded in eliminating selective disclosure at the cost of reducing the average quality of information. Collver (2007), using Hasbrouck summary informativeness statistic, found a significant decline in informed trading following Regulation FD for NYSE listed large capitalization firms. However, he found further evidence suggesting the decline not to be due to Regulation FD but due to decimalization. Gomes, Gorton and Madureira (2007) investigated the cost of capital after Regulation FD took effect and found that small firms were adversely affected by Regulation FD. They found a sharp decline in analyst coverage for some firms boosting cost of capital.

Overall, the bulk of the prior literature suggests that Regulation FD did not reduce the aggregate level of corporate disclosure or analysts' forecast accuracy. Given prior evidence that Regulation FD did not damage disclosure, this essay examines whether it had the desired effect of reducing earnings-related selective disclosure.

After Regulation FD took effect, corporations were prohibited from transmitting material nonpublic information to analysts. Given the restrictions that Regulation FD brought on the transmission of private information, I hypothesize that analysts' private information about upcoming earnings declined in the aftermath of Regulation FD. I use the association between analysts' recommendation revisions and subsequent earnings surprises to proxy for analysts' private information. While both public and private earnings-related disclosures are expected to trigger earnings forecast revisions, only selective disclosure is expected to affect analysts' recommendations. Further, even though firm executives can provide earnings guidance at any point in time, their private disclosures are likely to be more accurate in the period immediately before an earnings announcement. At this stage, managers are likely to possess a clear idea about the exact earnings that are going to be reported. If analysts have an early look at earnings results through selective disclosure they are more likely to revise their recommendations during this period.

The change in the association between analysts' revisions and subsequent earnings-announcement returns represents indirect evidence of the change in selective disclosure under the assumption that analysts' effort remains same across time. Therefore if Regulation FD was successful in reducing selective disclosure the association between recommendation revisions and earnings surprises is expected to weaken in the post-Regulation FD period.

H1: The association between the change in analysts' recommendations and subsequent earnings surprises weakened after Regulation FD took effect.

There is prior evidence that analysts' recommendation revisions during the week before earnings announcements generate greater impact than revisions made in other points in firms quarterly cycle. The difference in revision return is attributed to the potential burst of private information that analysts receive prior to earnings announcements. If Regulation FD was effective in reducing selective disclosure, then analysts' private information should be less, particularly in the pre-earnings-announcement period. Therefore, I hypothesize that the market impact difference generated by analysts' revisions in the pre- and non- earnings periods diminished after Regulation FD took effect.

H2: The difference in market reactions associated with analysts' recommendations revisions in the pre-earnings and non-earnings periods is lower in the post-Regulation FD period than in the pre-Regulation FD period.

3.3 Research Design

The period before an earnings announcement corresponds to a time in which firms are likely to have prepared financial statements and managers have the greatest knowledge of current quarter's earnings. If firm executives selectively disclose earnings-related information to analysts then this information is most likely to be privately communicated to analysts during the period before earnings announcements. Therefore to effectively measure analysts' earnings-related superior information I limit my sample to analysts' recommendation revisions in the pre-earnings announcement period. Specifically, I use analysts' recommendation revisions in the three-week period ending two-days before the earnings announcement.[5]

To assess whether Regulation FD reduced analysts superior knowledge of upcoming earnings results, I examine the association between analysts' pre-earnings-announcement recommendation revisions and subsequent earnings surprises during both pre- and post- Regulation FD periods. The association between recommendation revisions and subsequent earnings surprises is measured and compared across the pre-

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[5] The results remain qualitatively similar when I use a two-week or one-month period.

and post- Regulation FD periods using both univariate and multiple regression analysis.[6] Figure 3.1 provides an illustration of the timeline and the main association tests used in this study.

3.3.1 Univariate Analysis

In the univariate analysis, I measure and compare the mean earnings surprise associated with recently upgraded and downgraded firms in the pre- and post- Regulation FD periods. I calculate earnings surprises using four alternative methods: (1) standardized unexpected earnings based on time-series expectations, (2) standardized unexpected earnings based on analysts' expectations, (3) three-day earnings announcement abnormal return, and (4) two-day earnings announcement abnormal return.

Time-series unexpected earnings (SUE) are computed as follows:

$$SUE_{i,t} = \frac{e_t - e_{t-4}}{\sigma_{t,t-8}},$$

where e_t is firm i's earnings for quarter t and $\sigma_{t,t-8}$ is the standard deviation of earnings in the past eight fiscal-quarters. To control for common market-wide effects and avoid extreme values from biasing the results I standardize unexpected earnings by forming SUE deciles and transforming the variable to range between -0.5 and +0.5.

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[6] In early 2002, National Association of Securities Dealers (NASD) proposed Rule 2711and New York Stock Exchange (NYSE) proposed a modification to its Rule 472, Communications with the Public. The Securities and Exchange Commission (SEC) approved these proposals on May 8, 2002. Barber, Lehavy, McNichols and Trueman's (2006) results indicate that the approved proposals had a significant change in the distribution of analysts' buy recommendations during the first two calendar quarters of the year 2002. Since the changes in ratings during this period are likely to be due to changes in regulations, they may not necessarily reflect changes in analysts' private information. For robustness, I replicate all analyses excluding the first two calendar quarters of the year 2002. The results remain qualitatively similar when I exclude these quarters.

To compute analyst-expectation-based standardized unexpected earnings, I first compile analysts' earnings forecasts made after the previous quarter's earnings announcement date for each firm-quarter and retain the last earnings forecast of each analyst. Using the median of all analysts' latest earnings forecasts for a particular firm-quarter I measure the earnings expectation. I scale the difference between actual earnings and expected earnings by the price measured at the end of the previous fiscal-quarter. Specifically, I compute earnings surprises based on analysts' expectations as follows:

$$ASUE_{i,t} = \frac{e_t - \hat{e}_t}{p_t},$$

where e_t is firm i's actual earnings for quarter t and p_t is the firm's stock price at the end of quarter t-1 and $\hat{e}_t$ is the consensus earnings expectation. Finally to control for common market-wide effects and avoid extreme values from biasing the results I standardize unexpected earnings by forming ASUE deciles and transform it to range between -0.5 and +0.5.

I compute the abnormal return on the earnings announcement day as follows:

$$CAR_{i,t} = \sum_{m=-1}^{1} (R_{m,i,t} - Mkt_m),$$

where m is equal to 0 on firm i's quarter t earnings announcement date. $R_{m,i,t}$ is firm i's daily return on the mth day of quarter t's earnings announcement and Mkt_m is the CRSP NYSE/AMEX/Nasdaq value-weighted daily return for day m.

Brown and Warner (1985), using simulations, demonstrate that the choice of benchmark model leads to minor differences in abnormal returns when calculating short-term event window returns using daily returns. Since the computation of market adjusted returns does not require pre-event estimation period data and imposes the least data requirements, I present the empirical results based on market adjusted returns. However the results are similar when computing abnormal returns using market, three-factor or four-factor models as the normal return generating models.

To assess the association between revisions and earnings surprises I separately compute the mean earnings surprise that follows upgrades and downgrades in each quarter. Because recommendation revisions can be driven by market-wide information that affect numerous stocks, the earnings surprises that follow revisions may be correlated across stocks. Therefore, I follow the Fama and MacBeth (1973) procedure and compute mean earnings surprises based on quarterly results, obtain estimates of standard errors for pre- and post-FD periods and report results based on the mean difference across the two periods. Specifically, I first compute average earnings surprise for revisions within quarterly intervals and then compute the time-series means of the quarterly average surprises and the t-statistics using the time-series standard errors. The significance of the difference between pre- and post-FD periods is estimated using a mean comparison test which assumes unequal variances.

3.3.2 Regression Analysis

In addition to the univariate analysis, I implement a regression analysis to assess the difference in analysts' earnings-related private information across the pre- and post-Regulation FD periods. To measure the change in the association between recommendation revisions and subsequent earnings surprises I estimate the following regression models:

$$\begin{aligned} SSUE_{i,t} = {} & \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} \\ & + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

$$SASUE_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$CAR(-1,+1)_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t} \tag{3}$$

$$CAR(0,+1)_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t} \tag{4}$$

In the regression analyses, alternative earnings surprise measures are regressed on the mean recommendation revision for the quarter *(REV),* a Regulation FD indicator variable that takes a value of one for calendar-quarters during the post Regulation FD period *(POST_FD)* and the interaction of the mean recommendation revision and the Regulation FD indicator variables *(REV_FD)*. The coefficient of the *REV* variable tests whether the mean recommendation revision has predictive power of subsequent earnings surprises. The interaction of the *REV* and *POST_FD,* labeled *REV_FD* tests whether the association between analysts' revisions and subsequent earnings surprises declined in the aftermath of Regulation FD.

There are several potential confounding factors which may be correlated with analysts' revisions. Bernard and Thomas (1989) find that stock prices underreact to earnings announcements and this leads to a post-earnings announcement drift which is concentrated around subsequent earnings announcements. Therefore it is possible that analysts revise their recommendation ratings with respect to previous quarter's earnings results rather than their own information acquisition efforts or selective disclosure. To control for the potential effect of post-earnings-announcement drift on the results I include previous quarter's earnings announcement abnormal return *(LAG_ANCRET)* in the empirical model. To the extent that the market underreacts to previous quarter's earnings announcement, *LAG_ANCRET* will be positively correlated with current quarter's earnings surprise.

Further, Jegadeesh and Titman (1993) document that past returns have predictive power of future returns. Analysts', aware of the positive association between past and future returns, may make recommendation revisions accordingly and this may result in an association between revisions and subsequent earnings surprises. To control for momentum, I measure the three-month buy and hold return of the firm ending in the second month of the firm-quarter *(LRET)*.[7]

In addition, Sloan (1996) finds evidence that suggests investors fixate on bottom line earnings and ignore the accruals component of corporate earnings. He finds that accruals are negatively associated with subsequent year's abnormal returns and demonstrates that the mispricing is corrected particularly during subsequent quarterly earnings announcements. Since, previously announced accruals are negatively associated with subsequent earnings announcement returns, analysts may be revising recommendation ratings in response to past accruals rather than to their private communication with management. Therefore, I also control for the accrual component in the regression analysis. I compute accruals *(ACCR)* as in Sloan (1996) using the most recently announced annual reports.[8] The results are similar when I alternatively use discretionary accruals estimated from the modified Jones model (Dechow, Sloan and

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[7] I compute three-month returns ending at the end of the second month of the fiscal quarter to avoid a potential correlation between analysts' revisions during the pre-earnings-announcement period and returns. Nevertheless, the results are similar when I compute the buy-and-hold return during the fiscal-quarter.

[8] I assume that annual financial statements are filed within three months.

Sweeney (1995)), or from the performance-augmented modified Jones model (Kothari, Leone and Wasley (2005)) or using statement of cash flows data.

Finally, Ali, Durtschi, Lev and Trombley (2004) document that institutions have superior knowledge of upcoming earnings results and that institutional trades are positively correlated with subsequent earnings announcement returns. Again, it is possible that analysts' may be revising their recommendations amid institutional trades; hence revisions may be correlated with subsequent earnings surprises because analysts simply respond to contemporaneous institutional trading. To control for institutional trading I measure the change in institutional ownership during the most recent calendar quarter *(CHNG_IO)*. For detailed definitions of the variables used in the regression analysis please see Table 3.1.

3.3.3 Trading Strategy Analysis

In this analysis I estimate the performance of a trading strategy designed to capture the earnings announcement return differential between firms that were upgraded and downgraded during the pre-earnings announcement period. Ideally, the trading strategy should rely on analysts' recommendation revisions in the three-week period prior to the earnings announcement date. The trading strategy should purchase (sell short) shares of upgraded (downgraded) firms', one-day before the earnings announcement and liquidate positions at the end of the following day. Such a trading strategy cannot be implemented because upcoming earnings announcement dates are not available in event-time and prediction of announcement dates can be problematic.

As an alternative to the ideal trading strategy I estimate the performance of a strategy that purchases (sells) shares upgraded (downgraded) during the period after the fiscal-quarter-end but before the earnings announcement date and holds these shares until the end of the first day after the earnings are announced.[9] In this strategy all dates are known in event-time, hence no hindsight bias is introduced to the analysis.

To estimate the abnormal returns associated with such a trading strategy I first compute the daily raw returns that accrue to the trading strategy. I construct upgrade and downgrade portfolios. Each firm that is upgraded after the fiscal-quarter-end enters the upgrade portfolio one-day after the revision date and remains in the portfolio until one-day after the firm announces its quarterly earnings results. I calculate value-weighted daily returns for both upgrade and downgrade portfolios as follows:

$$R_{pt} = \sum_{j=1}^{n_{p,t-1}} x_{jt-1} R_{j,t},$$

where $R_{j,t}$ is the day t return on security j, $n_{p,t-1}$ is the number of firms in the portfolio and $x_{j,t-1}$ is the day t-1 market capitalization of firm j divided by the sum of day t-1 market capitalization of all the firms in the portfolio. The daily portfolio returns are then compounded to monthly returns as follows:

$$R_{pq} = \left[\prod_{t=1}^{n_t} (1 + R_{pt})\right] - 1$$

where n_t is the number of trading days in the month q and R_{pt} is the raw monthly return for the portfolio on day t.

I then construct a third portfolio that goes long on the upgrade portfolio and short on the downgrade portfolio. I compute this hedge portfolio's monthly returns using the difference between upgrade and downgrade portfolios' returns. Finally, I subtract the

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[9] All trades are initiated the following day of the recommendation revision.

risk-free rate from the upgrade and downgrade portfolios to compute the excess returns of the two portfolios. I do not subtract the risk-free rate from the hedge portfolio as this portfolio is a self financing portfolio.

I estimate the abnormal monthly return associated with the trading strategy by estimating the following four-factor model:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p Mkt_t + s_p SMB_t + h_p HML_t + u_p UMD_t + \varepsilon_{pt},$$

where Mkt_t is the market risk premium which is equal to market return minus the risk free rate, SMB_t is the average return on three small market capitalization portfolios minus the average return on three large market capitalization portfolios on day t, HML_t is the average return on two high book-to-market equity portfolios minus the average return on two low book-to-market equity portfolios for day t and UMD_t is the average of the returns on two (big sized and small sized) high prior return portfolios minus the average of the returns on two low prior return portfolios, where a big sized company is identified as being larger than the median NYSE market cap. The intercept of the above equation is used to test whether the portfolio is associated with abnormal returns.

3.4 Sample

The initial sample includes all firms traded in the New York (NYSE) and American (AMEX) exchanges and Nasdaq that have data available in both Center for Research in Security Prices (CRSP) and Compustat files.[10] The sample spans over the fiscal years 1995-2006 which corresponds to approximately six years of pre- and six years of post-

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[10] The merged Compustat/CRSP file (crsp.cstann) is used to construct the sample. CRSP monthly returns are obtained using the links between GVKEY (Compustat) and NPERMNO (CRSP) variables.

Regulation FD period data. The sample begins in the year 1995 because the IBES recommendation file is sparse for the period before 1994 and I require one-year of prior recommendation data to compute analysts' previous recommendations. The sample ends in the year 2006 because that is the latest fiscal year of annual financial statement data on Compustat files. I exclude closed-end funds, investment trusts, units and foreign companies. To avoid outliers from biasing the results all firms that have share prices below $1 at the end of the previous quarter are eliminated.

Analyst recommendations ratings are obtained from I/B/E/S (ibes.recddet). I eliminate all recommendations issued by anonymous analysts.[11] I identify a recommendation revision as the action of a particular analyst to change his/her prior recommendation rating. If a recommendation is revised to a more favorable (unfavorable) one, I identify it as an upgrade (downgrade).

I collect accounting data and earnings announcement dates from the Compustat quarterly files of the CRSP/Compustat merged database (crsp.cstqtr). Security return data is obtained from Center for Research in Security Prices (CRSP) files. For each firm I collect daily return data (crsp.dsf) adjusted for dividends, stock splits and delisting (using the delisting return provided in CRSP).

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[11] IBES does not provide a readily available revision variable. Therefore to compute recommendation revisions, analysts' prior and current recommendation ratings are necessary. I identify an analyst's prior recommendation rating by using IBES's analyst code and finding the analyst's previous recommendation rating. Since IBES assigns a code of 000000 for all anonymous analysts' it is not possible to compute recommendation revisions for anonymous analysts. Hence, I eliminate them from the sample. In untabulated results I assume that only one analyst in each broker covers the same firm and compute revisions based on the broker id and obtain similar results.

Analysts' quarterly earnings forecasts are obtained from the I/B/E/S unadjusted detail file (ibes.detu).[12] I adjust earnings estimates in the unadjusted detail file using CRSP's adjustment factor when necessary. To compute analyst's expectations I retain the last quarterly earnings forecast made by each analyst before the earnings announcement date and calculate the median of all earnings estimates.[13]

Finally, I obtain institutional ownership data from Thomson Financial's CDA/Spectrum Institutional (13f) Holdings database. I use the WRDS recreated shares outstanding to compute institutional ownership and I exclude observations where the filing and reporting dates are not equal to avoid erroneous observations from entering the sample.

Table 3.2 reports the descriptive statistics of the sample used in the study. The final sample consists of 31,244 firm-quarters and 4,853 unique firms. Due to the numerous data requirements (CRSP, Compustat, IBES, and TFN) imposed by the research design the final sample consists of a relatively small number of firm-quarters that include relatively large firms. The average firm in the sample has a market capitalization of $7 billion. The mean share price is $29 and the average beta is 1.08.

Finally, Table 3.3 reports the correlation matrix of the variables used in the multiple regression analysis. The four earnings surprise measures, SSUE, SASUE, CAR (-1, 1) and CAR (0, 1) are positively correlated, consistent with the fact that they are

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[12] I use the unadjusted detail file as opposed to the summary or the adjusted detail files because Payne and Thomas (2003) show that stock-split adjusted files do not have enough precision to unadjust the data without experiencing severe rounding errors.

[13] Only earnings estimates made after previous quarter's earnings announcement enter the sample.

measuring the same construct. However the correlation is not perfect, which emphasizes the need to analyze alternative earnings surprise measures for robustness.

The REV variable which is the mean revision during the three-week period before the earnings announcement period is positively correlated with earnings surprises. This is consistent with recommendation revisions having predictive power of subsequent earnings surprises. The LAG_ANCRET variable which is the previous quarter's three-day earnings announcement return is positively correlated with the four earnings surprise measures consistent with the post-earnings-announcement documented in Bernard and Thomas (1989). Further as suggested by the return momentum anomaly (Jegadeesh and Titman (1993)) LRET is positively correlated with the earnings surprise measures. The accrual component (ACCR), as found in Sloan (1996), is negatively correlated with subsequent earnings surprises. Finally, the CHNG_IO is positively correlated with subsequent earnings surprises. In short, the various control variables that are included in the multiple regression analysis are correlated with the earnings surprise measures as previously documented in the prior literature. Further, an extremely strong correlation among the independent variables that could suggest multicolinearity is not evident.[14]

3.5 Empirical Results

3.5.1 Univariate Analysis

Selective disclosure takes place when an analyst is informed by management about nonpublic material information. Private information received by analysts is likely to

[14] In addition to the correlation matrix, the variance inflation factors are computed to ascertain there is no multicolinearity issue in the regression analysis.

trigger an earnings forecast and recommendation rating change since the information is both material and not reflected in prices. On the other hand, public disclosure is unlikely to yield a recommendation change as the disseminated information is public and prices are expected to quickly reflect that information. Therefore, earnings forecasts are likely to be revised in response to both public and private information releases. In contrast, analysts' recommendations are more likely to be revised in response to private information. Therefore, the association between recommendation revisions and subsequent earnings surprises provides a cleaner test of selective disclosure. If Regulation FD was effective in reducing selective disclosure, the association between analysts' recommendation revisions and earnings surprises should decline in the aftermath of Regulation FD.

The univariate analysis reported in Table 3.4 examines the association between recommendation revisions and subsequent earnings surprises in the pre- and post-Regulation FD periods and tests whether the association between analysts' revisions and subsequent earnings surprises changed significantly after Regulation FD took effect. In Panel A of Table 3.4 we can see that in the Pre-Regulation FD period the mean earnings announcement return differential between upgraded and downgraded firms was 1.22 percent based on the three-day earnings announcement event window and 0.75 percent based on the two-day earnings announcement window. Similarly, the mean unexpected earnings difference between upgraded and downgraded firms were 6.94 and 6.35 percent using analyst based and time-series based expectations.[15] These results are consistent

[15] The earnings surprise differences are based on the decile differences.

with analysts' in the pre-Regulation FD period possessing superior knowledge of upcoming earnings results.

Overall, the mean earnings surprise differences between upgraded and downgraded firms, insensitive to the choice of earnings surprise calculation method, suggests the presence of some form of information acquisition or interpretation either through selective disclosure or effort was taking place. These results are consistent with pre-Regulation FD concerns that analysts were receiving early peeks at earnings results.

The second row of Panel A reports the strength of the relation between analysts' revisions and subsequent earnings surprises during the post-Regulation FD period. The mean three-day (two-day) earnings announcement return difference between recently upgraded and downgraded firms is 0.7 (0.34) percent in the post-Regulation FD period. Further, the mean earnings surprise difference between upgraded and downgraded firms based on analyst expectations and time-series expectations amounts to 4.19 and 2.79 percent in the post-Regulation FD data.

The final row of Panel A investigates whether the relation between revisions and subsequent earnings surprises declined after Regulation FD took effect. The results suggest that the mean three-day (two-day) earnings announcement return difference declined by 0.52 (0.34). The difference in both measures is statistically significant at the five-percent significance level. Consistent with the changes in earnings announcement returns, the earnings surprise measures based on analyst expectations and time-series expectations suggest a substantial decline in the association between revisions and earnings surprises. The change in analyst (time-series) earnings surprises differentials correspond to 2.75 (3.56) percent after Regulation FD took effect. Both values are statistically significant, reiterating the trend observed in the earnings announcement returns.

Overall the univariate results in Panel A suggest the association between revisions and earnings surprises to be significantly weaker in the post-Regulation FD period. These results are consistent with Regulation FD having reduced selective disclosure. These findings indirectly reveal that analysts received less private information about upcoming earnings from management. Consequently, analysts appear unable to make recommendation revisions that predicted earnings surprises as accurately as in the pre-Regulation FD period.

Panels B and C provide separate analyses based on upgrades and downgrades. Since individual analysis of upgrades and downgrades require splitting of the sample, these analyses involve a loss of power. For upgrades, the mean earnings surprises declines from 1.87 percent to 1.18 percent based on analyst expectations and from 3.64 percent to 2.33 percent based on time-series expectations. Although both reductions correspond to a substantial difference, 0.69% and 1.31%, the differences are not statistically significant. Similarly the earnings announcement return difference across the two periods remains statistically insignificant.

On the other hand for downgrades (in Panel C) the reported percentile difference between downgraded firms in the post Regulation FD period declines from -5.07% to -3.01% and the time-series based measure diminishes from -2.71% to -0.46%. Both differences based on analyst expectations and time-series expectations are statistically significant. Whereas, results based on earnings announcement returns are insignificant. Overall, Table 3.4 suggests a significant reduction in the earnings-related information conveyed through recommendation revisions between pre- and post- Regulation FD periods.

Analysts make recommendation revisions throughout firms' quarterly cycles. In the pre-Regulation FD period analysts were presumed to rely on private communications with firm executives to make recommendation and forecast revisions. As the earnings announcement date draws near, managers obtain a better idea of upcoming earnings and are more likely to provide private guidance. Finance theory stipulates the market impact associated with analysts' recommendation revisions to be a function of the private information involved in the revision. Then, recommendation revisions in the period prior to earnings announcements are likely to generate stronger market reaction than revisions that took place in other periods of the quarter. Further, if Regulation FD was effective in reducing selective disclosure, the difference between revisions in the pre-earnings period and other periods should diminish in the post-Regulation FD period.

Table 3.5 documents the announcement return differential (between pre-earnings and non-earnings periods) for three categories: (1) a hedge position that's long (short) on upgrades (downgrades), (2) upgrades and (3) downgrades in the pre- and post-Regulation FD periods. In Panel A, the mean market reaction differential between pre- and non-earnings periods for the hedge position are reported. Prior to Regulation FD, analysts' recommendation revisions generated 0.26 percent lower market reaction than revisions done in other points in time. The results range between -0.38 and -0.27 percent when other event windows are used to measure market impact, however none of the differences are significant.

Strikingly, in the post-Regulation FD period the market impact differential associated with revisions is -1.17 percent using a three-day event window and approximately -1.0 percent using two-, four- and five-day event windows. The negative market reaction differential associated with revisions in the pre-earnings-announcement period for the post-Regulation FD period is statistically significant. From these results it is evident that after Regulation FD took effect, recommendation revisions in the pre-earnings announcement period generated lower returns than revisions in other periods.

The final row of Panel A indicates that the differential associated with the timing of revisions declined by 0.91 percent for the (-1, +1) event window. The other event windows are similar. Overall, these results suggest that the private information value that market participants attributed to analysts pre-earnings-announcement period recommendation revisions declined significantly after Regulation FD took effect.

In Panels B and C, I separately investigate the premium associated with upgrades and downgrades. The results indicate a statistically significant decline in the relative value of both upgrades and downgrades. The relative value of upgrades using the three-day revision announcement return is -0.18% lower in the post- Regulation FD period. Similarly the (0, +1), (-2, +2), and (-1, +2) event window returns are significantly lower, ranging between -0.25% and 0.09%. The market reaction for downgrades is 0.59% higher in the post- Regulation FD period. This indicates that pre-earnings-announcement downgrades received lower premium after Regulation FD took effect. Similarly the alternative event window returns reiterate the finding from the three-day market reaction measure.

3.5.2 Regression Analysis

Post-earnings-announcement drift, return momentum, the accruals anomaly and/or institutional trading may be responsible for the apparent association between analysts' recommendation revisions and subsequent earnings surprises. It may be that analysts revise their recommendations in response to these predictive variables rather than to selective disclosure or their information acquisition activities.

Because of the potential correlation between these variables and analysts revisions, the univariate empirical results may be biased. Therefore in this section, I carry out a multiple regression analysis to test for the change in association between analysts' revisions and subsequent earnings surprises controlling for other potential confounding effects discussed in the research design section that may be correlated with analysts' recommendation revisions.

Table Table 3.6 reports the estimation results of equation (1). The results reported under the first specification indicate a positive association between mean recommendation revisions in the pre-earnings-announcement period and subsequent earnings surprises. The significantly positive coefficient is consistent with prior univariate results. Further, the *REV_FD* variable, which is the interaction of the *REV* and *POST_FD* variables, is significantly negative. The negative loading on the *REV_FD* variable suggests that the association between recommendation revisions and subsequent earnings surprises declined in the post-Regulation FD period. In the second specification I regress the earnings surprise measure additionally on previous quarter's earnings announcement return *(LAG_ANCRET)* and past three-months (ending in the second month of the fiscal-quarter) buy and hold return *(LRET)* to control for post-earnings announcement drift and return momentum. As in the first specification the *REV_FD* is significantly negative reiterating the decline in analysts' superior knowledge of upcoming earnings results.[16] Further, consistent with prior literature coefficients on the *LAG_ANCRET* and *LRET* are positive suggesting the presence of post-earnings-announcement-drift and return momentum.

In the third specification, I include an accruals term to control for the accrual anomaly documented by Sloan (1996). The accrual term, *ACCR*, receives a negative loading as expected and the *REV_FD* coefficient remains significantly negative while controlling for accruals. In the final specification, I include the change in institutional ownership to control for the association between institutional trading and subsequent earnings announcement returns documented by Ali et al. (2004). The inclusion of the change in institutional ownership factor does not alter the results and *REV_FD* continues to receive a significantly negative loading. These results suggest that analysts' private information of upcoming earnings declined in the post-Regulation FD period. In Table 3.7, I report the estimation results of equation (2) which regresses earnings surprises based on analyst expectations on other confounding factors. I obtain similar results using earnings surprises calculated from analyst expectations as opposed to a time-series model. The *REV_FD* coefficient is estimated to be significantly negative under all four specifications.

Table 3.8 reports the estimation results of equation (3) where cumulative abnormal returns computed from the three-day period centered on the earnings

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[16] For robustness, I also estimate this and remaining models using firm fixed effects, the results remain similar.

announcement day are regressed on mean recommendation revisions and other confounding factors. The results echo the previous findings from the time-series and analyst based results. The *REV_FD* interaction variable is significantly negative, suggesting a substantial decline in the association between mean recommendation revisions and subsequent earnings surprises measured as the abnormal return during the three-day centered on the earnings announcement day.

Finally, Table 3.9 reports the regression analysis of two-day abnormal returns beginning on the earnings announcement day. The results are consistent with prior results and reiterate the existence of a significant decline in the association between recommendation revisions and earnings surprises during the post-Regulation FD period.

3.5.3 Trading Strategy Analysis

In this sub-section I examine the abnormal returns associated with a trading strategy designed to capture analysts' superior knowledge of upcoming earnings results during the pre- and post- Regulation FD periods. The trading strategy goes long (short) on firms that are upgraded (downgraded) after the fiscal-quarter-end and held until one-day after the earnings announcement day.[17]

I estimate the abnormal returns accrued by such a trading strategy during the pre- and post- Regulation FD periods and report the results in Table 3.10. The hedge strategy that goes long (short) on upgraded (downgraded) firms during the pre-earnings-

[17] Different from the prior analysis, only recommendation revisions after the fiscal-quarter-end as opposed to the three-week period prior to the earnings announcement date are taken into account because the earnings announcement day is not available in event-time. The results are similar when I assume knowledge of upcoming earnings announcement dates and use a three-week cutoff period.

announcement period accrues a monthly abnormal return of 4.6% before transaction costs during the pre-Regulation FD which is significant at the one-percent significance level. On the other hand the identical trading strategy does not accrue significantly positive abnormal returns during the post-Regulation FD period. The decline in the performance of the trading strategy is consistent with the decline in analysts' superior knowledge of upcoming earnings results.

The remainder of Table 3.10 reports separate results for the upgrade and downgrade portfolios. While both upgrade and downgrade portfolios accrue significantly positive returns in the pre-Regulation FD period, neither portfolio significantly outperforms the market in the post-Regulation FD period.

The trading strategy that was investigated in this section involves significant transaction costs due to the high turnover nature of the strategy. Nevertheless, it provides a comparison of the private information associated with analysts' revisions during the pre- and post- regulation FD periods. The results, overall, suggest a significant decline in analysts' superior knowledge of upcoming earnings results in the post-Regulation FD period. This is consistent with the univariate and regression analyses presented in this study.

3.6 Conclusion

This paper investigates whether firms' earnings-related selective disclosure declined in the aftermath of Regulation FD. Selective disclosure about upcoming earnings was one of the most publicized cases of unfair disclosure. A significant number of comment letters expressed frustration on the basis of the belief that corporations were giving private earnings guidance to select analysts or investors.

The empirical results suggest that analysts' private information about upcoming earnings surprises declined significantly after Regulation FD took effect. Prior to Regulation FD, recently upgraded firms reported earnings surprises (time-series SUE) that were on average 6.35 percent greater than downgraded firms. In the post Regulation FD period the earnings surprise difference between upgraded and downgraded firms declined more than 50 percent to 2.79 percent. Similarly, earnings announcement return difference between upgraded and downgraded firms dropped roughly 50 percent from 1.22 percent to 0.7 percent. These results are consistent with Regulation FD having reduced selective disclosure and analysts' earnings-related private information.

3.7 Tables for Chapter 3

Table 3.1 Variable Definitions
This table lists and defines the variables used in this study. The first column indicates the variable label as used in the tables and the second column provides the definition

Variable	Definition
SSUE	Quarterly decile of unexpected earnings defined as ($e_t - e_{t-4}$) scaled by the standard deviation of unexpected earnings ($\sigma_{t,t-8}$). e, EPS is basic earnings-per-share excluding extraordinary items (Compustat data item #19), adjusted for stock splits and stock dividends. The variable is transformed to range between -0.5 and +0.5.
SASUE	Quarterly decile of unexpected earnings defined as actual earnings reported by IBES minus median earnings estimate of analysts scaled by the price at the end of the previous fiscal-quarter. The deciles are transformed to range between -0.5 and +0.5.
CAR (-1, +1)	Cumulative market-adjusted returns during three-day period centered on the earnings announcement date. The CRSP NYSE/AMEX/Nasdaq value weighted index return is used as the market return. Returns are adjusted for delisting.
CAR (0, +1)	Cumulative market-adjusted returns during two-day period beginning on the earnings announcement date. The CRSP NYSE/AMEX/Nasdaq value weighted index return is used as the market return. Returns are adjusted for delisting.
REV	The mean of recommendation revision made during the three-week period ending two-days before the earnings announcement date.
POST_FD	An indicator variable that takes a value of one for fiscal-quarters ending after October 23rd, 2000 and zero for prior fiscal-quarter end-date.
LAG_ANCRET	Previous fiscal-quarter's earnings announcement return which is defined as the cumulative market-adjusted returns during three-day period centered on the earnings announcement date. The CRSP NYSE/AMEX/Nasdaq value weighted index return is used as the market return. Returns are adjusted for delisting.
LRET	The three-month buy and hold return ending at the end of the fiscal quarter's second month.
ACCR	ΔCA- ΔCL - DEP scaled by average total assets where ΔCA is the change in Current Assets (Compustat annual data item #4) minus the change in cash and short-term investments (item #1), ΔCL is the change in current liabilities (item #5) minus the sum of changes in debt in current liabilities (item #34) and income taxes payable (item #71). DEP is depreciation and amortization (item #14).
CHNG_IO	The change in institutional ownership percentage compiled from the

Table 3.2 Descriptive Statistics

The initial sample consists of the intersection of the CRSP, Compustat, IBES and TFN databases. The sample spans over the fiscal years 1995-2006; corresponding to approximately six-years of pre- and six-years of post-Regulation FD period data. Closed-end funds, investment trusts, units, foreign companies and firms that have share prices below $1 at the end of the previous quarter are eliminated. The final sample includes 31,224 firm-quarters and 4,853 unique firms. Market Value is based on the price at the end of previous quarter calculated from CRSP share prices and shares outstanding. Price is the end of previous quarter share price reported in CRSP. Book-to-market ratio is market value divided by common equity [data60/(data25Xdata199)] computed using the most recent annual data (assuming a three-month reporting lag). Earnings Annc. Return - CAR (-1, +1) is the three-day cumulative market-adjusted returns on the earnings announcement date.

	Mean	Std.	10th Percentile	25th Percentile	75th Percentile	90th Percentile
Market Value (in millions)	7,128,106	23,476,848	148,745	394,500	4,317,162	14,124,971
Price	29.03	24.46	6.88	13.56	38.61	55.88
Beta	1.08	0.65	0.37	0.63	1.43	1.96
Book-to-Market Ratio	0.426	0.457	0.112	0.211	0.562	0.816
Earnings Annc. Return - CAR (-1, +1)	0.003	0.090	-0.089	-0.036	0.043	0.095

Table 3.3 Correlation Table

Pearson correlations (above) and spearman correlations (below) are reported for the four earnings surprise measures and the control variables in the multiple regression analysis. SSUE is the standardized unexpected earnings decile based on time-series earnings expectation model, SASUE is the standardized unexpected earnings decile based on analyst expectations. Both SSUE and SASUE variables are transformed to range between -0.5 and +0.5. CAR(-1, 1) and CAR(0, 1) variables are the three-day and two-day market-adjusted earnings announcement returns. REV is the mean revision during the pre-earnings three-week period ending two-days before the earnings announcement. LAG_ANCRET is the previous quarter's three-day market-adjusted earnings announcement return. LRET is the three-month buy and hold return ending on the second month of the fiscal-quarter. ACCR is total accruals computed as in Sloan (1996) and scaled by average total assets. CHNG_IO is the change in institutional ownership percentage during the most recent calendar-quarter.

Variable	*SSUE*	*SASUE*	*CAR (-1, 1)*	*CAR (0, 1)*	*REV*	*LAG_ANCRET*	*LRET*	*ACCR*	*CHNG_IO*
SSUE	1	0.220	0.087	0.083	0.051	0.114	0.136	-0.050	0.036
SASUE	0.219	1	0.210	0.205	0.083	0.086	0.139	-0.058	0.021
CAR (-1, 1)	0.099	0.233	1	0.903	0.042	0.016	0.017	-0.009	0.000
CAR (0, 1)	0.091	0.223	0.866	1	0.033	0.009	0.018	-0.010	0.003
REV	0.056	0.085	0.048	0.034	1	0.020	0.058	-0.019	0.007
LAG_ANCRET	0.123	0.082	0.007	-0.001	0.015	1	0.319	-0.005	0.013
LRET	0.150	0.136	0.005	0.007	0.052	0.291	1	-0.033	0.009
ACCR	-0.047	-0.056	0.000	-0.001	-0.021	0.004	-0.024	1	-0.015
CHNG_IO	0.040	0.027	-0.001	-0.001	0.013	0.013	0.007	-0.014	1

Table 3.4 Recommendation Revisions and Subsequent Earnings Surprises

This table reports the mean earnings surprises that follow analysts' recommendation revisions made in the three-week period prior to earnings announcements (-23, -2). Earnings surprise is measured and reported based on (1) the median of the most recent earnings forecasts of analysts, (2) the time-series earnings expectation, (3) the market-adjusted three-day earnings announcement return centered on the report date, and (4) the market-adjusted two-day earnings announcement return beginning on the report date. Earnings announcement returns are winsorized at the bottom and upper one-percentile. The mean and standard error of earnings surprises are computed using the Fama and MacBeth (1973) procedure based on quarterly means. Panel A reports results for the earnings surprise difference between upgrades and downgrades for the pre- and post-Regulation FD periods and the final row tests for the difference in means, assuming unequal variances. Panels B and C report results separately for upgrades and downgrades.

Period	Unexpected Earnings (Analyst Exp.)	Unexpected Earnings (Time Series)	Market-Adj. Earnings Announcement Return CAAR (-1, +1)	Market-Adj. Earnings Announcement Return CAAR (0, +1)
Panel A: Upgrades - Downgrades				
Pre Regulation FD	6.94%	6.13%	1.25%	0.80%
	(10)	(6.46)	(8.46)	(5.98)
Post Regulation FD	4.44%	3.03%	0.64%	0.25%
	(6.85)	(4.4)	(3.55)	(1.76)
Pre- vs. Post- Reg. FD	2.49%	3.10%	0.61%	0.54%
	(2.63)	(2.65)	(2.62)	(2.79)
Panel B: Upgrades				
Pre Regulation FD	2.03%	3.66%	1.00%	0.53%
	(5.01)	(4.34)	(8.08)	(5.24)
Post Regulation FD	1.49%	2.87%	0.61%	0.24%
	(2.83)	(2.77)	(4.33)	(1.97)
Pre- vs. Post- Reg. FD	0.54%	0.79%	0.39%	0.29%
	(0.82)	(0.59)	(2.07)	(1.83)
Panel C: Downgrades				
Pre Regulation FD	-4.90%	-2.48%	-0.26%	-0.27%
	(-8.48)	(-3.2)	(-1.39)	(-1.95)
Post Regulation FD	-2.96%	-0.16%	-0.03%	-0.01%
	(-4.69)	(-0.19)	(-0.14)	(-0.06)
Pre- vs. Post- Reg. FD	-1.95%	-2.32%	-0.23%	-0.25%
	(-2.28)	(-2.03)	(-0.78)	(-1.11)

Table 3.5 Incremental Value of Revisions Made Before Earnings Announcements
This table reports the difference in mean returns of revisions made in the pre-earnings-announcement period and non-earnings periods. Returns are computed based on (-1, +1), (0, +1), (-2, +2) and (-1, +2) event windows and winsorized at the bottom and upper one-percentile. The mean and standard error of returns are computed using the Fama and MacBeth (1973) procedure based on quarterly means and reported below. Panel A reports the value of upgrades and downgrades prior to earnings announcements relative to revisions made in other periods separately for the pre- and post- Regulation FD periods. The final row compares the difference in means across the two periods and reports t-statistics assuming unequal variances. Panels B and C report results separately for upgrades and downgrades.

Period	Market-Adj. Recommendation Revision Return CAAR (-1, +1)	Market-Adj. Recommendation Revision Return CAAR (0, +1)	Market-Adj. Recommendation Revision Return CAAR (-2, +2)	Market-Adj. Recommendation Revision Return CAAR (-1, +2)
Panel A: Upgrades - Downgrades				
Pre Regulation FD	-0.26%	0.38%	-0.27%	-0.35%
	(-0.73)	(1.44)	(-0.7)	(-0.94)
Post Regulation FD	-1.17%	-0.76%	-1.29%	-1.13%
	(-4.37)	(-3.54)	(-4.31)	(-3.99)
Pre- vs. Post- Reg. FD	-0.91%	-1.14%	-1.02%	-0.79%
	(-2.07)	(-3.33)	(-2.08)	(-1.69)
Panel B: Upgrades				
Pre Regulation FD	-0.18%	0.09%	-0.25%	-0.15%
	(-0.93)	(0.67)	(-1.11)	(-0.74)
Post Regulation FD	-0.72%	-0.46%	-0.80%	-0.70%
	(-4.51)	(-3.63)	(-4.08)	(-4.19)
Pre- vs. Post- Reg. FD	-0.54%	-0.55%	-0.55%	-0.56%
	(-2.18)	(-2.93)	(-1.86)	(-2.16)
Panel C: Downgrades				
Pre Regulation FD	0.08%	-0.29%	0.03%	0.20%
	(0.27)	(-1.37)	(0.08)	(0.66)
Post Regulation FD	0.45%	0.30%	0.50%	0.43%
	(1.87)	(1.67)	(1.89)	(1.7)
Pre- vs. Post- Reg. FD	0.37%	0.59%	0.47%	0.23%
	(0.99)	(2.12)	(1.11)	(0.58)

Table 3.6 Regression Analysis of Subsequent Earnings Surprises – Time-Series Exp.
This table reports the estimation results of the empirical model:

$$SSUE_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t}$$

where SSUE is the standardized unexpected earnings decile based on a time-series earnings expectation model. REV is the mean recommendation revision during the pre-earnings-announcement period of quarter t of firm i, POST_FD is a post-Regulation FD indicator variable, and REV_FD is the interaction of REV and POST_FD variables. LAG_ANCRET is the previous quarter's three-day earnings announcement return (market-adjusted), LRET is the past three-month buy and hold return ending a month before the fiscal quarter end. ACCR is total accruals scaled by average total assets as in Sloan (1996) and CHNG_IO is the change in percentage ownership during the most recent calendar-quarter. Four specifications of the above model are estimated. T-statistics are reported in parentheses.

Model	Intercept	REV	POST_FD	REV_FD	LAG_ANCRET	LRET	ACCR	CHNG_IO	Obs.	R-Square
I	0	0.027	0.015	-0.015	-	-	-	-	25,761	0.45%
	(0.1)	(8.7)	(3.39)	(-3.89)						
II	-0.008	0.024	0.018	-0.013	0.296	0.124	-	-	25,761	2.90%
	(-2.35)	(7.72)	(4.22)	(-3.45)	(12.31)	(16.89)				
III	-0.014	0.023	0.016	-0.013	0.297	0.122	-0.169	-	25,761	3.08%
	(-3.83)	(7.59)	(3.63)	(-3.38)	(12.37)	(16.66)	(-6.83)			
IV	-0.014	0.023	0.015	-0.013	0.295	0.122	-0.166	0.191	25,761	3.25%
	(-3.95)	(7.52)	(3.38)	(-3.32)	(12.3)	(16.69)	(-6.73)	(6.8)		

Table 3.7 Regression Analysis of Subsequent Earnings Surprise – Analysts Exp.
This table reports the estimation results of the empirical model:

$$SASUE_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t}$$

where SASUE is the unexpected earnings decile based on the consensus analyst expectation. REV is the mean recommendation revision the pre-earnings-announcement period of quarter t of firm i, POST_FD is a post-Regulation FD indicator variable, and REV_FD is the interaction of REV and POST_FD variables. LAG_ANCRET is the previous quarter's three-day earnings announcement return (market-adjusted), LRET is the past three-month buy and hold return ending a month before the fiscal quarter end. ACCR is total accruals scaled by average total assets as in Sloan (1996) and CHNG_IO is the change in percentage ownership during the most recent calendar-quarter. Four specifications of the above model are estimated. T-statistics are reported in parentheses.

Model	Intercept	REV	POST_FD	REV_FD	LAG_ANCRET	LRET	ACCR	CHNG_IO	Obs.	R-Square
I	-0.004 (-1.37)	0.031 (12.89)	0.005 (1.49)	-0.013 (-4.15)	-	-	-	-	29,455	0.85%
II	-0.01 (-3.9)	0.027 (11.63)	0.008 (2.21)	-0.011 (-3.64)	0.162 (8.42)	0.117 (20.51)	-	-	29,455	3.08%
III	-0.015 (-5.6)	0.027 (11.47)	0.004 (1.18)	-0.011 (-3.57)	0.163 (8.5)	0.115 (20.18)	-0.174 (-9.06)	-	29,455	3.35%
IV	-0.015 (-5.67)	0.027 (11.42)	0.004 (1.02)	-0.011 (-3.54)	0.162 (8.45)	0.115 (20.19)	-0.173 (-9.01)	0.082 (4.01)	29,455	3.41%

Table 3.8 Regression Analysis of Subsequent Earnings Surprise – CAR (-1, 1)
This table reports the estimation results of the empirical model:

$$CAR(-1,1)_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t}$$
$$+ \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t}$$

where CAR(-1,1) is the three-day market-adjusted earnings announcement return. REV is the mean recommendation revision the pre-earnings-announcement period of quarter t of firm i, POST_FD is a post-Regulation FD indicator variable, and REV_FD is the interaction of REV and POST_FD variables. LAG_ANCRET is the previous quarter's three-day earnings announcement return (market-adjusted), LRET is the past three-month buy and hold return ending a month before the fiscal quarter end. ACCR is total accruals scaled by average total assets as in Sloan (1996) and CHNG_IO is the change in percentage ownership during the most recent calendar-quarter. Four specifications of the above model are estimated. T-statistics are reported in parentheses.

Model	Intercept	REV	POST_FD	REV_FD	LAG_ANCRET	LRET	ACCR	CHNG_IO	Obs.	R-Square
I	0.005	0.004	-0.004	-0.002	-	-	-	-	30,302	0.20%
	(6.27)	(5.88)	(-3.52)	(-2.14)						
II	0.005	0.004	-0.004	-0.002	0.007	0.001	-	-	30,302	0.21%
	(6.1)	(5.79)	(-3.47)	(-2.1)	(1.26)	(0.85)				
III	0.005	0.004	-0.004	-0.002	0.008	0.001	-0.011	-	30,302	0.22%
	(5.61)	(5.75)	(-3.66)	(-2.08)	(1.27)	(0.78)	(-1.91)			
IV	0.005	0.004	-0.004	-0.002	0.007	0.001	-0.011	0.005	30,302	0.22%
	(5.6)	(5.74)	(-3.69)	(-2.08)	(1.26)	(0.78)	(-1.9)	(0.75)		

Table 3.9 Regression Analysis of Subsequent Earnings Surprise – CAR (0, 1)
This table reports the estimation results of the empirical model:

$$CAR(0,1)_{i,t} = \alpha + \beta_1 REV_{it} + \beta_2 POST\_FD_{i,t} + \beta_3 REV\_FD_{i,t} + \beta_4 LAG\_ANCRET_{i,t} + \beta_5 LRET_{i,t} + \beta_6 ACCR_{i,t} + \beta_7 CHNG\_IO_{i,t} + \varepsilon_{i,t}$$

where CAR(0,1) is the two-day market-adjusted earnings announcement return beginning on the earnings announcement date. REV is the mean recommendation revision the pre-earnings-announcement period of quarter t of firm i, POST_FD is a post-Regulation FD indicator variable, and REV_FD is the interaction of REV and POST_FD variables. LAG_ANCRET is the previous quarter's three-day earnings announcement return (market-adjusted), LRET is the past three-month buy and hold return ending a month before the fiscal quarter end. ACCR is total accruals scaled by average total assets as in Sloan (1996) and CHNG_IO is the change in percentage ownership during the most recent calendar-quarter. Four specifications of the above model are estimated. T-statistics are reported in parentheses.

Model	Intercept	REV	POST_FD	REV_FD	LAG_ANCRET	LRET	ACCR	CHNG_IO	Obs.	R-Square
I	0.002 (2.53)	0.003 (4.9)	-0.002 (-1.68)	-0.002 (-2.09)	-	-	-	-	30,302	0.11%
II	0.002 (2.36)	0.003 (4.81)	-0.002 (-1.64)	-0.002 (-2.06)	0.002 (0.4)	0.002 (1.33)	-	-	30,302	0.12%
III	0.002 (1.98)	0.003 (4.78)	-0.002 (-1.81)	-0.002 (-2.04)	0.002 (0.4)	0.002 (1.27)	-0.009 (-1.69)	-	30,302	0.13%
IV	0.002 (1.97)	0.003 (4.76)	-0.002 (-1.85)	-0.002 (-2.03)	0.002 (0.39)	0.002 (1.27)	-0.009 (-1.68)	0.006 (0.93)	30,302	0.13%

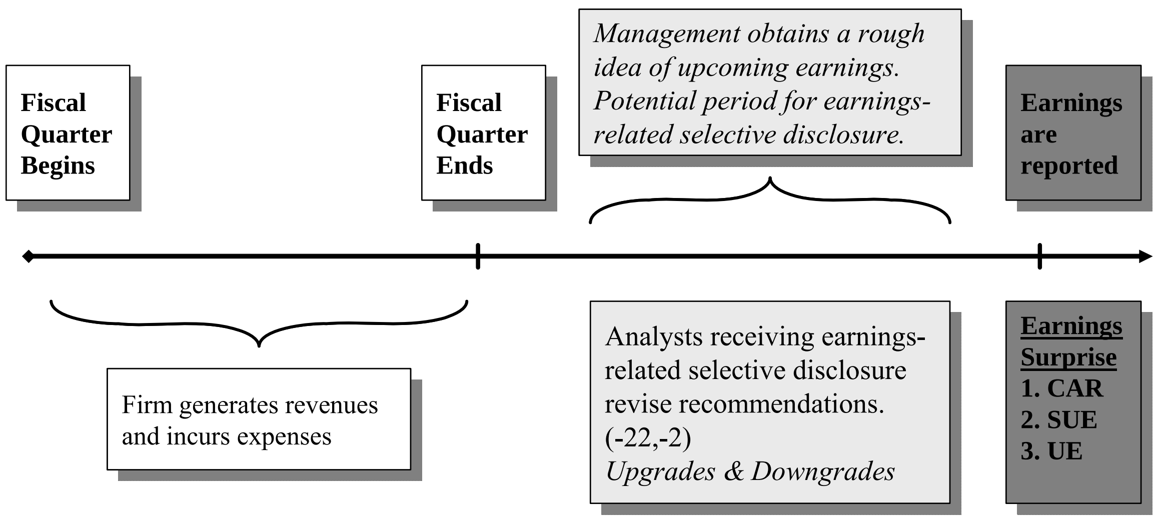
Table 3.10 Trading Strategy Performance and Characteristics

This table reports the performance and characteristics of the trading strategy that purchases (sells) and holds shares upgraded (downgraded) after fiscal-quarter-end until the end of the first day after the earnings announcement. The portfolio performance and characteristics reported are based on a time-series regression of each portfolio's excess monthly return on the four factors: excess market return (Beta - 4th column), a zero-investment size portfolio (SMB - 5th column), a zero-investment book-to-market portfolio (HML - 6th column) and a zero investment momentum portfolio (UMD - 7th column). The intercept of this equation which is an estimate of the abnormal return is reported for each portfolio in the third column. The R square and adjusted R square values of the time-series regressions are reported on the last column. Numbers in parentheses are the t-statistics of the estimated coefficients above them.

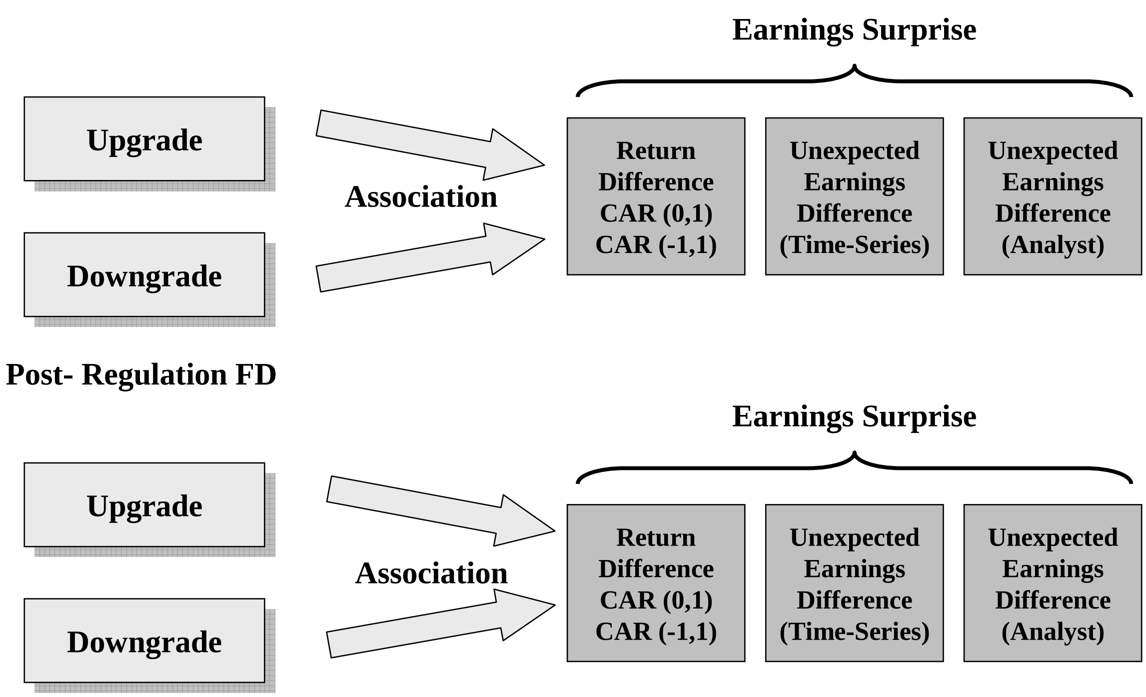
Portfolio	Period	Intercept	Beta	SMB	HML	UMD	R-square	Adj. R-square
Hedge	Pre-Regulation FD	0.046	-0.053	-0.242	-0.056	-0.294	11.2%	4.3%
		(4.52)	(-0.2)	(-0.99)	(-0.13)	(-1.22)		
Hedge	Post-Regulation FD	0.023	0.050	0.257	0.054	0.142	1.5%	-5.3%
		(1.92)	(0.16)	(0.66)	(0.14)	(0.61)		
Upgrade	Pre-Regulation FD	0.027	0.995	0.086	-0.224	-0.271	46.4%	42.2%
		(3.18)	(4.64)	(0.43)	(-0.65)	(-1.36)		
Upgrade	Post-Regulation FD	0.015	1.421	0.381	-0.018	0.297	37.2%	32.9%
		(1.29)	(4.63)	(1.03)	(-0.05)	(1.35)		
Downgrade	Pre-Regulation FD	-0.019	1.048	0.328	-0.168	0.023	47.5%	43.5%
		(-1.96)	(4.2)	(1.4)	(-0.42)	(0.1)		
Downgrade	Post-Regulation FD	-0.009	1.370	0.123	-0.072	0.155	55.0%	51.9%
		(-1.09)	(6.52)	(0.49)	(-0.28)	(1.02)		

3.8 Figures for Chapter 3

Figure 3.1 Research Design
This figure is a visual depiction of the research design. The first panel describes which analyst recommendation revisions are included in the analysis with respect to the quarterly cycle of the firm. Panel B illustrates the main test of the paper and lists which earnings surprise measures are used.
Panel A: Timeline of the empirical analysis



Panel B: Association test for the pre- and post- Regulation periods



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