Why do analysts revise their stock recommendations after earnings announcements?

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Abstract

During earnings announcements, managers disclose a variety of information that leads to changes in expectations of future earnings and share prices. To the extent that share prices fully reflect new information, earnings announcements are not expected to create opportunities for market participants to detect mispricing. However, analysts often advise their clients to trade in response to earnings announcements. Nearly a quarter of all analysts' recommendation revisions occur within the three-day period after earnings are announced. This paper examines why such a large fraction of recommendation revisions are concentrated after earnings announcements. The empirical analyses suggest that recommendation revisions are more concentrated after earnings announcements when there is greater mispricing and when it is harder for analysts to obtain information from alternative sources. In addition, recommendation revisions are more concentrated after earnings announcements for firms with more complex information and informative earnings. Further, examination of how analysts revise their stock recommendations using earnings information shows that analysts revise their recommendations in the direction of the earnings surprise measured based on their own and consensus estimates. However, analysts give more weight to consensus expectations than their own forecasts. Also, analysts appear to assign less weight to earnings surprises when consensus expectations are likely to have been achieved through expectation management and when the earnings information confirms analysts' prior opinions. Finally, earnings announcements coupled with recommendation revisions exhibit higher earnings response coefficients consistent with a more efficient pricing of earnings information.

Keywords: financial analysts, stock recommendations, earnings announcements, information interpretation versus information discovery.

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1. Introduction

Nearly a quarter of all financial analysts' recommendation revisions take place within the three-day period following earnings announcements. The concentration of recommendation revisions is puzzling given that earnings announcements are public disclosures. Efficient market hypothesis posits that it is not possible for investors to earn abnormal profits by trading in response to earnings announcements because public information is instantaneously incorporated into share prices. However, analysts frequently advise their clients to trade based on information conveyed in earnings announcements.

Presumably, analysts issue recommendations based on a comparison of their own valuation with the market's valuation. When analysts' valuation is significantly greater than the market's valuation, analysts are expected to issue favorable recommendations and when it is significantly less, they are expected to issue unfavorable recommendations. A significant change in an analyst's valuation, due to new *public* information (e.g. earnings announcements) is not necessarily expected to warrant a stock recommendation revision because the new information is likely to have already been incorporated into market prices. Therefore the new information is not expected to affect analysts' value-to-price comparison. Nevertheless, 23.1 percent of recommendation revisions are concentrated shortly after earnings announcements (trading days 0, 1 and 2).

This paper examines *why* and *how* analysts revise their recommendation ratings in response to earnings announcements and whether recommendation revisions contribute to the pricing of earnings. Examining these research questions aims to improve our understanding of the informational and firm-specific characteristics that induce analysts to issue new recommendations based on public information. Accordingly, the findings of this paper shed light on the factors that contribute to analysts' ability to process public information in a manner that produces private information. In addition, examining how analysts respond to earnings announcements in the form of recommendation revisions intends to improve our understanding of how sell-side analysts use accounting information in their valuations to revise their recommendations and give advice to their clients. Finally, the investigation of the relation between analysts' recommendations following earnings announcements and the pricing of earnings aims to expand our knowledge of the role that analysts play in facilitating market efficiency.

In order to determine why analysts revise their recommendations after earnings announcements, I measure the concentration of recommendation revisions after earnings announcements at a firm-quarter level and explore factors that contribute to the variation in the concentration. Prior evidence on the post-earnings announcement drift suggests that investors fail to fully incorporate earnings information into prices (Ball and Brown 1968, Bernard and Thomas 1989 and Livnat and Mendenhall 2006). Therefore, it is possible that financial analysts use public information released in earnings announcements to make informed recommendation revisions. Conversely, analysts may be strategically revising their recommendations to improve the perceived profitability of their recommendations. In addition, financial analysts are sophisticated market participants trained and specialized in understanding the operations of the companies that they cover. Even though earnings disclosures are made available to the general public, it may be difficult for ordinary investors to interpret and process these disclosures. This effect is likely to be more pronounced for firms with complex information. For these firms, analysts may be able to apply their superior information processing skills to produce private information based on earnings disclosures. Further, analysts who follow companies with less information availability are more likely to rely on earnings announcements to issue recommendations because they have fewer sources of information. Therefore, the scarcity of public information may lead to the concentration of recommendation revisions after earnings announcements. Finally, analysts are more likely to revise their recommendations after earnings announcements issued by firms with more informative earnings. Since the key driver of stock recommendations is the valuation of the company, information signals that have stronger implications for valuation are more likely to be associated with changes in recommendation ratings. This study examines the extent to which the factors above influence the concentration of recommendation revisions after earnings announcements.

As the second objective, this paper examines how analysts use earnings information to revise their recommendations. The examination of how analysts use earnings information calls for an analyst-firm-quarter level analysis. Upon receiving earnings information, analysts can either compare the reported earnings to the consensus expectation or to their own earnings forecasts. To the extent that analysts rely more on their own forecasts to develop valuations and issue recommendations, a stronger relation between recommendation revisions and earnings surprises based on their own forecast is expected. In contrast, if analysts rely more on the consensus expectations to estimate their valuation models, we expect analysts' recommendation revisions to be more strongly correlated with the earnings surprise measure based on the consensus expectation. Bartov et al. (2002) and Matsumoto (2002) show that managers, at times, avoid negative earnings surprises by managing analysts' earnings expectations downwards. While downward expectation management can help firms achieve earnings targets, it also reduces the quality of earnings surprises because targets are achieved in part by lowering expectations. I examine whether analysts recognize expectation management activities and place less weight on earnings surprises when there is a greater probability of expectation management. Further, Altinkilic and Hansen (2009) propose strategic timing of revisions to enhance perceived stock picking performance as an explanation for the concentration of recommendations after news. They carry out various tests to rule out alternative explanations. This paper conducts a direct test of the explanation proposed in Altinkilic and Hansen (2009) by examining whether the association between analysts' recommendation revisions and earnings surprises is stronger for analysts' with poorer past stock picking performance. If analysts time their recommendations to enhance their perceived stock-picking performance, analysts with poorer past performance, who are also in greater need for improvement in their performance, are more likely to time their recommendations after earnings announcements with large earnings surprises. Finally, I examine how analysts react to contradictory information released in earnings announcements. Specifically, I test whether analysts place higher or lower emphasis on earnings surprises when the earnings surprise contradicts their prior recommendation rating.

The final analysis of this paper examines whether analysts' recommendations contribute to the pricing of earnings information. In order to examine this issue, I follow a similar approach to that of Zhang (2008) and identify firm-quarters where at least one analyst issued a recommendation revision within two days after the earnings announcement date (0, 1). I then examine the earnings response coefficient and post-earnings-announcement returns associated with firm-quarters that have recommendation revisions following earnings announcements

Analyzing the determinants of the timing of analysts' recommendation revisions reveals that financial analysts revise their recommendation after earnings announcements when they perceive their information processing skills to be superior, when they have less information available from sources other than earnings and when earnings are more informative. The analyst-firm-quarter level analysis suggests that analysts determine the direction and magnitude of their recommendation revisions conditional on the earnings surprise and place significantly greater weight (approx. 108%) on the consensus earnings expectation than on their own earnings forecast. Also, analysts appear to recognize expectation management activities and place considerably less weight on earnings surprises when earnings targets are likely to have been achieved through expectation management. In addition, analysts with poor past stock picking performance are more likely to revise their recommendations in line with recent earnings surprises. This is consistent with Altinkilic and Hansen's (2009) conclusion that analysts strategically time their recommendations to enhance their stock picking performance. Further, analysts react more strongly to earnings announcements when earnings surprises contradict their prior recommendation rating. Finally, I find that earnings announcements coupled with recommendation revisions have higher earnings response coefficients and post-earnings announcement returns than firm-quarters without recommendation revisions. These results suggest that analysts contribute to the pricing of earnings information. However, investors only partly react to the information revealed in analysts' recommendation revisions.

This paper contributes to the literature by shedding light on the puzzling finding of recommendation revisions being concentrated after earnings announcements (Ivkovic and Jegadeesh 2004). Conrad et al. (2006) examine recommendation revisions issued in response to large price changes and find that analysts behave as if they have private information. Consistent with their findings, I show that mispricing, information availability and complexity and earnings informativeness are significant determinants of the concentration of recommendations after earnings announcements. This study also contributes to our understanding of how sell-side analysts use earnings information to issue recommendation ratings. Pioneering work by Finger and Landsman (2003) and Bradshaw (2004) analyze the relation between recommendation ratings and earnings forecasts. Finger and Landsman (2003) find that recommendation changes are positively related to analysts' forecasts. Bradshaw (2004) finds that recommendation ratings are positively associated with PEG model-based valuation estimates and uncorrelated or negatively correlated with residual income model based valuations derived from analysts' earnings forecasts. This study documents new evidence relating to the weight that analysts place on their forecasts versus the consensus expectations, analysts' reaction to expectation management and how analysts act in response to contradictory information. The empirical analysis provides corroborating evidence to Altinkilic and Hansen's (2009) inference that analysts' strategically time their recommendation revisions. Finally, this paper contributes to the literature by extending prior work that examines analyst responsiveness. Stickel (1989) and Zhang (2008) examine the timing of earnings forecasts and document several key determinants of analysts' timing. Earnings forecasts reflect analysts' estimates of next period financial results, whereas recommendation ratings provide analysts' opinion of the degree of mispricing. While earnings forecasts are expected to follow the arrival of public information, recommendation revisions are not expected unless analysts are able to produce private information. Examining responsiveness based on recommendation revisions provides results that complement Stickel (1989) and Zhang's (2008) research and reveal new insights on the extent to which analysts react to earnings announcements in the form of identifying mispricing and issuing recommendation revisions.

The remainder of this paper is organized as follows. The next section discusses the sample selection and provides descriptive statistics. Sections 3 and 4 present the firm-quarter and analyst-firm-quarter level analyses, respectively. Section 5 examines the relation between market efficiency and analysts' recommendation timing and Section 6 concludes.

2. Data and descriptive statistics

The initial sample, based on the CRSP & Compustat merged file, for the period 1994Q1-2010Q4, consists of 347,134 firm-quarters with non-missing earnings announcement dates. Combining the initial sample with the I/B/E/S database and excluding firm-quarters without a recommendation revision reduces the sample to 107,035 firm-quarters.[1] Merging the intersection of CRSP, Compustat and I/B/E/S with the CDA/Spectrum database to obtain institutional ownership data further limits the sample to 106,923 firm-quarters. The final sample consists of 88,797 firm-quarters which have the necessary accounting and market data to construct the control variables employed in the regression analysis.

The sample contains firm-quarter observations from each major industry in the CRSP, Compustat and I/B/E/S universe. Table 1, Panel A shows the industry composition of the final sample. All industries, based on the Fama and French (1997) 49 industry classification scheme, are represented in the final sample. The largest share of observations comes from the Banking industry (7,838 observations) and the smallest share comes from the Real Estate industry (90 observations). The

[1] Recommendation revisions are merged with fiscal quarters based on the period between three days after the previous quarter's earnings announcement date and two days after the current quarter's earnings announcement date.

number of observations per year increases fairly consistently moving from the year 1994 to 2010. Table 1, Panel B reports the number of observations per fiscal year. For fiscal year 1994, the number of firm-quarters that meet the data requirements is 3,668 and for fiscal year 2010 it is 5,361.

Table 2 reports the summary statistics for the final sample. The average firm in the sample has close to $5 billion market capitalization, is followed by roughly 10 analysts, and has been public for approximately 19 years. The mean proportion of recommendation revisions (*REVCONC*) that occur after earnings announcements is 23.1 percent while the median is zero. The difference between the mean and median indicates a skewed distribution where a large portion of the firm quarters do not possess any recommendation revisions after earnings announcements. This suggests that a large fraction of recommendation revisions occur after earnings announcements for a relatively small portion of the firm quarters. The mean and median absolute unexpected earnings (|S*UE*|) are both close to zero. The dummy variable for Regulation FD (*FD*) has a mean of 0.650 indicating that 65 percent of the firm-quarters in the final sample belong to the period after Regulation FD was enacted. Finally, the average firm invests 5.7 percent of its sales in research and development, has a book-to-market ratio of 0.517 and has 2.172 segments. The average earnings response coefficient for the firm-quarters in the sample is 9.559.

Table 3 presents the correlation matrix for the variables employed in the regression analysis. The highest correlation reported among the independent variables is between *LOGMV* and *COV* and is 0.66. The high correlation between the two variables is consistent with the prior literature that documents that larger firms have greater analyst coverage (Bhushan 1989). In order to ensure that the estimation results are unaffected by correlations among the independent variables I examine variance inflation factors and also include the two variables separately in the regression model.

3. Firm-level determinants of the concentration of recommendation revisions after earnings announcements

3.1 What drives analysts to revise their recommendations after public announcements?

Analysts presumably issue favorable recommendations when they value the company to be considerably higher than the market's valuation and unfavorable recommendations when they value the company to be below the market's valuation. Womack (1996) describes stock recommendations as analysts stating that "I have analyzed the publicly available information, and the current stock price is not 'right'" (p. 164). In response to the inflow of new information, analysts revise their valuations and issue recommendation decisions based on the difference between their valuation and the market's valuation. A significant change in an analyst's valuation due to new public information should not necessarily trigger a stock recommendation revision because that information is likely to have been incorporated into share prices and hence is not expected to affect the disparity between the market's and analyst's valuations.

On earnings announcements, managers, through public disclosures, release a wide array of information. The public nature of the earnings disclosure facilitates an instantaneous adjustment in share prices that incorporates new information. Since both analysts and investors are concurrently made aware of the same information, on average, an equal level of change in analysts' and market's valuation of the corporation is expected to occur. Therefore, the adjustment in share prices and analysts' valuations is unlikely to yield a significant change in the difference between analysts' and market valuations. For example, suppose that an analyst, who has a neutral recommendation rating on a company, estimates the value of that company to be $1 million and the market has the same valuation. The public disclosure of a new piece of information that implies a 10 percent increase in the company's valuation will cause both the market capitalization and the analyst's valuation to increase by 10 percent from $1 million to $1.1 million. Such a change will leave the difference between the analyst's valuation and the market's valuation unaffected, in this case at zero. Since analysts are expected to issue recommendations based on the extent to which their valuations diverge from the market's valuation, the arrival of *public* information (e.g. earnings) is unlikely to affect analysts' recommendations.

In contrast, Ivkovic and Jegadeesh (2004) find that a large proportion of recommendation revisions take place within a few days after earnings announcements. They interpret the concentration of revisions as surprising and indicate that, "If market prices fully react to the information in earnings, then there is no reason to expect public announcements of earnings to trigger recommendation revisions" (p. 444).

3.1.1 Earnings Surprise

One explanation for the concentration of recommendation revisions after earnings announcements is that market prices *do not* fully react to information in earnings and that analysts exploit this inefficiency. In other words, analysts may be revising their recommendations after earnings announcements because they identify mispricing. Ball and Brown (1968), Bernard and Thomas (1989), Chan et al. (1996), Livnat and Mendenhall (2006) and others show that some portion of the earnings information is not instantaneously incorporated into share prices, leading prices to drift in the direction of the earnings surprise during the next three-month period. They find that when firms are sorted into deciles based on earnings surprises, firms in the decile with the largest positive earnings surprise outperform firms in the decile with the largest negative earnings surprise. Therefore, it is possible that analysts revise their recommendations because they predict a drift to follow earnings announcements. I investigate this possibility by testing whether recommendation revisions are more concentrated after announcements of earnings with larger earnings surprises (*DSUE*).

H1. The concentration of recommendation revisions is higher for firm-quarters with larger earnings surprises.

3.1.2 Information availability

Recommendation revisions after earnings announcements may be more probable when analysts have limited or no information from alternative sources. Larger (*LOGMV*) and older (*AGE*) firms as well as firms with greater analyst coverage (*COV*) have richer information environments. Thompson et al. (1987) and Fang and Peress (2009) find that larger firms attract significantly greater press coverage than smaller firms. The greater coverage from the press is likely to increase the supply of interim information and reduce the monopoly of earnings announcements as a source of information. Further, Grant (1980) and Atiase (1985) document evidence consistent with investors of smaller firms having fewer sources, other than earnings announcements, from which to obtain information on firms. The superior information environment present in larger, older and widely followed firms is likely to provide analysts with greater opportunities to acquire information from sources other than earnings announcements. Therefore, in these firms, analysts are less likely to rely on earnings announcements to issue recommendations. Conversely, in cases where analysts have less access to information, earnings announcements may represent a more critical opportunity for analysts to issue recommendations by processing public information.

An additional measure of information availability is constructed based on the comparison of the period before and after the passage of Regulation Fair Disclosure (FD) which took effect on October 23rd, 2000. Regulation FD prohibited managers from selectively disclosing information to analysts, thereby limiting the amount of information that analysts receive from sources other than earnings announcements (Gintschel and Markov 2004). The restrictions that Regulation FD imposed are likely to have elevated the importance of earnings announcements and increased the concentration of recommendation revisions after earnings announcements. Therefore, I predict that as the inflow of information from sources other than earnings during the quarter decreases, analysts are more likely to time their recommendation revisions after earnings announcements.

H2. The concentration of recommendation revisions after earnings announcements is inversely associated with information availability.

3.1.3 Information Complexity

Analysts are equipped with the skills necessary to process complex information that ordinary investors may have difficulty processing. For instance, interpreting the disclosure made by a pharmaceutical firm regarding the current status of their drugs in the pipeline can be more challenging for ordinary investors than for analysts with the relevant experience and training. Barron et al. (2002) find evidence consistent with analysts' earnings forecasts containing higher proportions of private information for R&D intensive firms and analysts being more effective at complementing the financial reports of these companies. In addition, Palmon and Yezegel (2011) argue that analysts are better equipped with the skills necessary to analyze R&D intensive firms and they find that analysts issue more valuable recommendations for R&D intensive firms. Therefore, analysts may find opportunities to issue recommendations when analyzing disclosures made by R&D intensive companies (*DRND*). Similarly, growth firms (*B/M*) and firms that have a greater number of segments (*LOGSEGMENT*) also represent opportunities for analysts because these firms pose additional challenges for ordinary investors to process information due to the uncertain and complex nature of their businesses. Further, firms that were recently involved in mergers and acquisitions (*MERGER*), restructuring (*SPECIAL*) or missed earnings expectations (*NEGSURP*) are likely to have earnings that are less persistent, more uncertain and more difficult for ordinary investors to interpret. The comparative advantage that analysts possess in processing complex information can help them identify mispricing based on complex public disclosures and issue recommendation revisions. To empirically test the validity of this prediction, I test the hypothesis that the concentration of recommendations after earnings announcements is positively associated with information complexity.

H3. The concentration of recommendation revisions after earnings announcements is higher for companies that disclose more complex information.

3.1.4 Informativeness of earnings

The informativeness of earnings announcements is another factor that may affect the concentration of recommendation revisions after earnings announcements. Earnings announcements are expected to have less impact on firm valuation when they are less informative. To the extent that analysts perceive the markets to be inefficient in processing earnings information, a larger fraction of analysts are expected to revise their recommendations after earnings announcements of firms with higher earnings response coefficients (*ERC*). Therefore, I test the hypothesis that posits a positive association between the informativeness of earnings announcements and the concentration of recommendation revisions.

H4. The concentration of recommendation revisions after earnings announcements is positively associated with the informativeness of earnings announcements.

3.1.5 Demand for analysts' advice

Finally, an incentive for analysts to revise their recommendations ratings is to meet investors' demand for timely advice on firm valuation. Investors rely on analysts' advice in making trading decisions and institutional investors pay particular attention to analysts' reports to make informed decisions and to fulfill their fiduciary duties. While analysts can provide an assessment of the financial performance within their reports without a recommendation rating revision, a revision provides the most direct and concise form of communication. The demand for timely information is greater for firms with larger institutional ownerships (*INST*) because of the magnitude of the investments that these institutions posses and their ability to influence analysts' decisions. Commission revenues generated from institutional investors and *Institutional Investor* rankings which are based on portfolio managers' votes represent important incentives for analysts (O'Brien and Bhushan 1990). To the extent that institutional ownership exerts greater demand on the timely release of analysts' opinion, a greater concentration of recommendation revisions is expected to follow earnings announcements of companies with larger ownership by institutional investors.

H5. The concentration of recommendation revisions is greater for firms with greater institutional ownership.

3.2 Empirical analysis

3.2.1 Methodology

In order to measure the concentration of recommendation revisions issued in response to earnings announcements, I first compute the total number of revisions issued during the period beginning three days after the previous fiscal quarter's earnings announcement date and ending two days after the current earnings announcement date. I then classify recommendation revisions issued on the day of the earnings announcement and the two days after, as issued in response to earnings announcements. Then I compute the ratio of the number of recommendation revisions issued after earnings announcements and the total number of recommendation revisions to measure the concentration of recommendation revisions after earnings announcements (*REVCONC*).

The regression model below examines the relation between the concentration of recommendation revisions after earnings announcements and proxies for (1) earnings surprise, (2) information availability, (3) information complexity, (4) earnings informativeness and (5) demand for analysts' advice:

$$\begin{aligned} REVCONC_{it} = \alpha &+ \beta_1 DSUE_{it} + \beta_2 FD_{it} + \beta_3 LOGMV_{it} + \beta_4 COV_{it} + \beta_5 AGE_{it} + \beta_6 LOGSEGMENT_{it} \\ &+ \beta_7 DRND_{it} + \beta_8 B/M_{it} + \beta_9 MERGER_{it} + \beta_{10} SPECIAL_{it} + \beta_{11} NEGSURP_{it} + \beta_{12} ERC_{it} \\ &+ \beta_{13} INST_{it} + \varepsilon_{it}, \end{aligned} \tag{1}$$

$REVCONC_{it}$	=	The proportion of recommendation revisions issued within the three-day period (0,2) after firm *i*'s fiscal quarter *t* earnings announcement.
$DSUE_{it}$	=	Decile ranking of the absolute value of standardized unexpected earnings. Standardized unexpected earning is computed as actual earnings minus the median earnings forecast divided by share price as of the previous fiscal quarter's end-date.
FD_{it}	=	Dummy variable that takes a value of one for fiscal quarters that end after October 23rd, 2000.
$LOGMV_{it}$	=	Natural logarithm of the market value of the firm at fiscal quarter end-date.
COV_{it}	=	The number of analysts who issued an earnings estimate for the fiscal quarter.
AGE_{it}	=	The number of years that the firm existed in the CRSP database.
$LOGSEGMENT_{it}$	=	Natural logarithm of the number of segments that the company operates in.
$DRND_{it}$	=	Decile ranking of the ratio of research and development expenditure to net sales.
B/M_{it}	=	The ratio of book equity and market value as defined in Daniel and Titman (2006).
$MERGER_{it}$	=	Dummy variable that takes a value of one for firms that engaged in a merger or acquisition during the fiscal year.
$SPECIAL_{it}$	=	Dummy variable that equals one for fiscal quarters in which the firm reported negative special items.
$NEGSURP_{it}$	=	Dummy variable that equals one for fiscal quarters when the firm missed earnings expectations.
ERC_{it}	=	The coefficient of unexpected earnings in the ERC model where earnings announcement returns, CAR (-1, +1), are regressed on unexpected earnings scaled by price, based on 20 historical fiscal quarter data requiring a minimum of eight fiscal quarters.
$INST_{it}$	=	The percentage of shares held by institutional investors as of the most recent calendar quarter prior to fiscal quarter *t* of firm *i*.

The post-earnings announcement drift literature documents a positive relation between earnings surprises and subsequent three-month abnormal returns. In order to capture the earning surprise information, I compute unexpected earnings scaled by share price as of the previous fiscal quarter's end-date, UE_{it}. I then use the decile ranking of the absolute value of unexpected earnings (*DSUE*) in the regression model because both positive and negative earnings surprises are associated with future abnormal returns.

Prior to the acceptance of Regulation Fair Disclosure (FD), managers could privately communicate with analysts and provide them information. After Regulation FD took effect, managers were required by law to disclose nonpublic material information to all stakeholders at the same time. Gintschel and Markov (2004) and others document evidence suggesting that Regulation FD reduced the amount of information that was privately communicated to analysts. The reduction in selective disclosure inevitably increased analysts' reliance on public information (e.g., earnings) as a source of information. In order to capture the level of information privately available to analysts, I use a dummy variable (*FD*) that takes a value of zero for firm-quarters prior to Regulation FD and one otherwise. This measure proxies for the change in private information availability and allows the testing of the effect of the change in information availability on the concentration of recommendation revisions. In addition, I use analyst coverage (*COV*) as another proxy for the extent of information availability. Firms that are followed by more analysts have a greater supply of information because more analysts are working to acquire and process information. Further, there is more information available for firms that are larger and for those that have been operating for longer periods of time. It is easier for analysts to acquire information on such companies in periods other than earnings announcements. I therefore use the natural logarithm of market capitalization (*LOGMV*) and firm age (*AGE*) to proxy for information availability.

Companies that are involved in a greater number of business lines require more effort for analysts to acquire and interpret information. These companies tend to be more complex and require more rigorous information processing skills. In order to incorporate this aspect of the information environment, I compute the natural logarithm of the number of segments that a company operates in, $LOGSEGMENT_{it}$, and employ it in the regression model. Growth firms and firms that are involved in intangible intensive industries tend to have lower book-to-market ratios. The unique nature of these companies makes them more difficult to analyze and value. Therefore, I use the ratio of book-to-market

(B/M_{it}) as a proxy for firm complexity. Similarly, firms that are on the forefront of new technology invest heavily in research and development. Ordinary investors are likely to find it challenging to process information disclosed by these firms due to the uncertain nature of their R&D investments as well as the complexity of their businesses. Therefore, I use the decile ranking of the ratio of research & development expenditures and sales ($DRND_{it}$) as another measure for information complexity. Finally, firms that were recently involved in mergers and acquisitions (*MERGER*), restructuring (*SPECIAL*) or missed earnings expectations (*NEGSURP*) are likely to have earnings that are less persistent, more uncertain and harder for ordinary investors to interpret (Hong et al. 2000 and Zhang 2008).

The earnings response coefficient (*ERC)* variable captures the extent to which earnings announcements are informative. The earnings response coefficient is estimated based on a regression of market-adjusted earnings announcement returns on standardized unexpected earnings for the past twenty fiscal quarters. Finally, the institutional ownership level (*INST*) is included to capture the level of demand for analysts' timely advice.

The dependent variable of the above regression is the percentage of all recommendation revisions that occur within the three day period after earnings announcements and ranges between zero and one. In order to ensure that the predicted values from the regression also have values that range between zero and one, I estimate the above equation using a generalized linear model with a logit link and binomial family. Since a firm in the sample may have more than one fiscal quarter, I rely on firm-clustered standard errors to reach inferences regarding statistical significance. As a robustness check, I re-estimate the analyses using ordinary least squares (OLS), Fama and MacBeth (1973) and random-effects generalized least squares (GLS) approaches.

3.2.2 Results

The estimation results suggest that analysts are more likely to revise their recommendation ratings in the three day period following earnings announcements with larger earnings surprises (*DSUE*). Table 4 reports the estimation results of equation (1). In Model 1, the concentration of recommendation revisions (*REVCONC*) is regressed on the decile of the absolute value of standardized unexpected earnings (*DSUE*). The coefficient of *DSUE* is estimated to be 0.214 (p<0.01). The positive association suggests that as the degree of earnings surprise increases, the concentration of recommendation revisions within the three-day period after the earnings announcement also increases. The magnitude of the coefficient implies that firm-quarters in the top absolute earnings surprise decile have recommendations revisions that are 16.4 percent more concentrated following earnings announcements than firm-quarters in the bottom absolute earnings surprise decile.

In Model 2, the dependent variable (*REVCONC*) is regressed on *DSUE* and also on proxies intended to capture information availability: *FD*, *LOGMV*, *COV* and *AGE*. *FD* is a dummy variable that takes a value of one for fiscal quarters after Regulation Fair Disclosure (FD) was enacted. *LOGMV, COV* and *AGE* variables represent firm size, analyst coverage and firm age, respectively. Table 4, Model 2 reports the coefficient of *FD* to be 0.516 (p<0.01). The positive coefficient suggests that after Regulation FD, the concentration of recommendation revisions after earnings announcements increased 40.4 percent. The increase in the concentration of recommendation revisions after Regulation FD is consistent with analysts relying more heavily on earnings announcements to revise their recommendations. This finding is consistent with analysts being more inclined to revise their recommendations after earnings announcements because of the contraction in the amount of information that is available to them from sources other than earnings announcements. Similarly, the coefficients of *LOGMV*, *COV* and *AGE* variables are all estimated to be negative and statistically significant. Firms that are larger, older and that have greater analyst coverage possess richer information environments because of their importance to the general economy and the scrutiny that they receive from the financial community, the government and the press. The results indicate that as firm size, analyst coverage and firm age increase, the concentration of recommendation revisions after earnings announcements decreases. This finding is consistent with analysts relying more on information other than earnings announcements to revise their recommendations ratings for larger, older and more widely followed firms.

In Model 3, I examine the relation between information complexity and recommendation revision concentration while controlling for earnings surprise and information availability. Six variables are employed to capture various factors that are associated with information complexity. The coefficients of *LOGSEGMENT*, *DRND*, *B/M*, *MERGER, SPECIAL* and *NEGSURP* are estimated to be 0.023 (p<0.1), 0.214 (p<0.01), -0.096 (p<0.01), 0.058 (p<0.01), -0.097 (p<0.01) and 0.062 (p<0.01), respectively. These results suggest that recommendation revisions are more concentrated following earnings released by firms that have a higher number of segments, larger investment in research and development and lower book-to-market ratios. In addition, firms that recently underwent merger/acquisitions or experienced negative earnings surprises exhibit greater concentration of recommendation revisions. Surprisingly, firms with negative special item earnings exhibit less concentrated recommendation revisions. The results, with the exception of *SPECIAL,* suggest that as information complexity increases, analysts are able to process public information in a manner that yields recommendation revisions. In cases where firms announce negative special item earnings, analysts appear to be less inclined to issue recommendation revisions. This runs counter to the argument proposed earlier and suggests that analysts avoid issuing recommendation revisions when special items are reported. However, the majority of the results indicate recommendation revision concentration to be positively associated with information complexity. These results suggest that analysts perceive their information processing skills to be superior when valuing firms with complex information.

Next, the relation between the concentration of recommendation revisions (*REVCONC*) and earnings informativeness (*ERC*) is examined. Model 4 presents the estimation results of the empirical model with the inclusion of the earnings response coefficient (*ERC*) variable. The coefficient of *ERC* is estimated to be 0.003 (p<0.01). The positive ERC coefficient suggests that as earnings informativeness increases, the concentration of recommendation revisions after earnings announcements also increases. The positive association between the informativeness of earnings and the post-earnings concentration of revisions is consistent with analysts reacting more strongly to earning releases that have greater valuation implications.

In Model 5, the institutional ownership level (*INST*) is included to examine the relation between the demand for analysts' recommendation and the concentration of recommendation revisions. The estimation results reported in Table 4, Model 5 reveal that the coefficient of the *INST* variable is not statistically significant. This finding suggests that the demand for analysts' opinion on earnings in the form of recommendations does not significantly affect the concentration of recommendation revisions. The absence of pressure on analysts from institutional investors may be due to the ability of institutional investors to process earnings information in-house, thereby reducing their reliance on prompt advice from analysts.

In summary, the empirical results show that mispricing, information availability, information complexity and earnings informativeness influence the variation in the concentration of recommendation revisions. Analysts are more likely to revise their recommendations when they predict a higher level of post-earnings announcement drift. This behavior is consistent with analysts attempting to take advantage of the post-earnings announcement drift to help their clients earn profits. Such a relation may also be the result of analysts' strategic timing. I examine this possibility in the next section. Further, recommendation revisions are more heavily concentrated after earnings announcements for firms where analysts have less access to information from sources other than earnings announcements. This result is consistent with analysts being more likely to use information communicated through earnings announcements when they have less opportunities to collect information from alternative sources. Recommendation revisions are also more concentrated following earnings announcement of firm-quarters involving the release of more complex information. This indicates that analysts leverage their information processing skills to interpret earnings announcements and issue recommendations. Finally, analysts are more inclined to revise their recommendations in response to earnings announced by firms that have more informative earnings announcements (higher earnings response coefficients). I find no evidence suggesting a positive association between revision concentration and institutional ownership.

Table 5 reports the results of estimating equation (1) using different estimation methods to check for robustness. In Model 1, the results based on ordinary least squares (OLS) estimation are reported. These findings are similar to the findings based on the generalized linear model (GLM) estimation results reported in Table 4. Hypotheses 1-4 are largely supported. The results provide no support for Hypothesis 5 as in the earlier analysis. In Model 2, the OLS results using firm and fiscal quarter clustered standard errors are reported. The results again are similar. The only difference pertains to the coefficient of *LOGSEGMENT* which is not found to be statistically significant. However, other measures of information complexity (*DRND, B/M, MERGER* and *NEGSURP*) continue to support the inference that recommendation revisions are more concentrated after earnings announcements of firms with more complex information. In Model 3, I re-estimate the model using the Fama and MacBeth (1973) procedure. The Fama and MacBeth (1973) procedure involves the estimation of the same model each period and averaging of the coefficient estimates across all periods. Since the *FD* variable is a time variable it is constant within each period and therefore cannot be included in the model. The results based on Fama and MacBeth regression are identical to the ones based on OLS with double-clustered standard errors. Hypotheses 1-4 are largely supported and no evidence is found in support of Hypothesis 5. Finally, in column 4 I re-estimate the empirical model using random-effects GLS regression. The results are similar to the initial results. The only difference relates to the coefficient of the firm size variable (*LOGMV*). In model 4, firm size is not estimated to be statistically significant whereas in the initial estimation results firm size was found to be statistically significant. The divergence in the results appears to be due to the correlation between firm size and analyst coverage. In untabulated analyses, I exclude the coverage variable (*COV*) from the empirical model and find firm size (*LOGMV*) to be statistically significant while other variables have the same signs. In conclusion, the robustness check analysis indicates that the results are insensitive to the estimation method and that the data largely support hypotheses 1-4 regardless of the estimation method.

4. How do analysts' react to earning announcements?

This section examines how analysts use information released in earnings announcements to issue recommendation revisions. Various aspects of the decision making process leading to recommendation revisions remain unexplored. Prior research on the determinants of analysts' recommendations shows that analysts respond to major news (proxied by large price changes) by issuing new recommendations ratings (Conrad et al. 2006), that analysts recommendation ratings are more strongly related to valuation estimates based on the PEG models than based on residual income models (Bradshaw 2004), and that recommendation revisions are consistent with forecasts and factors known to predict future returns and contemporaneous news (Finger and Landsman 2003). This section extends the prior literature by focusing on the effect of earnings information on the direction and magnitude of analysts' recommendation revisions. Specifically, I examine whether analysts rely more on their forecasts or on the consensus expectation when they revise their recommendations and how expectation management, analysts' past stock-picking performance and the contradictory versus confirmatory nature of earnings affect analysts' decision to revise their recommendations in response to earnings announcements. Overall, this analysis intends to improve our understanding of various factors that analysts take into account when they revise their recommendations.

4.1 Analyst's own earnings forecasts versus the consensus expectations

An important task that financial analysts perform is to forecast the earnings of companies that they cover. Earnings forecasts are closely followed by the financial community. Data vendors such as Thomson Reuters, Bloomberg and others regularly aggregate analysts' individual earnings forecasts to compute consensus earnings expectations and release these figures to the general public. Investors pay attention to consensus expectations and earnings announcement returns correlate positively with the difference between reported and expected earnings.

When evaluating earnings announcements, analysts can compare reported earnings to their forecast and/or to the consensus earnings expectation. To the extent that analysts use their own forecasts in generating stock recommendations, analysts' post-earnings announcement recommendation revisions are expected to be more strongly correlated with the earning surprise based on their own forecast than the earnings surprise based on the consensus earnings expectation. Conversely, if analysts place greater emphasis on the consensus expectations, we expect analysts' recommendation revisions to be more strongly correlated with the earnings surprise measure based on the consensus expectations. It is unclear, ex ante, which component analysts would place greater emphasis on. Therefore, I test the non-directional hypothesis that analysts assign equal weight to their own earnings forecasts and to the consensus earnings expectations.

H6. Analysts place equal weight on the consensus earnings expectation and their own earnings forecast while revising their recommendations in response to earnings announcements.

4.2 Earnings expectation management

Bartov et al. (2002) and Matsumoto (2002) find evidence consistent with managers guiding analysts' earnings forecasts to avoid missing earnings expectations. Bartov et al. (2002) show that investors reward firms that achieve earnings targets. Further they show that the premium assigned to firms that meet/exceed earnings targets also exists for firms that are likely to have achieved targets via expectation management.

I examine whether analysts react differently to earnings surprises when earnings expectations are likely to have been achieved via expectation management. Analysts are better positioned to detect expectation management because it is their forecasts that have been influenced by managers. Thus, analysts who revised their forecasts downward or observed other analysts who did so because of information received from managers are more likely to identify cases where expectation management occurred. In light of the adverse effect of expectation management on earnings surprise quality, I expect analysts to place less weight to earnings surprises that are likely to have been achieved via expectation management than earnings surprises attained without expectation management. Therefore, the association between changes in recommendations and standardized unexpected earnings is expected to be weaker for firm-quarters involving expectation management.

H7. The association between recommendation revisions and earnings surprises is weaker for firms that are likely to have achieved earnings expectations through expectation management.

4.3 Piggybacking on earnings information

An alternative possibility is that analysts revise their recommendations in reaction to earnings surprises in order to piggyback on market-moving information. Altinkilic and Hansen (2009) find that analysts' recommendation revisions often follow recent news. They further suggest that analysts, by strategically issuing recommendations on days of public disclosures, enhance the perceived profitability of their recommendations. This is because institutions that evaluate analysts generally measure recommendation profitability by cumulating security returns starting on the day (or one day before) the recommendation was issued. For instance, the *Wall Street Journal*, when measuring the profitability of analysts' recommendations, begins to accrue the returns starting on the day that the recommendation was issued. This feature of the performance measurement methodology provides analysts with the opportunity to first observe the earnings announcement and then revise their recommendation ratings accordingly. As an example, suppose that firm ‘A’ announces earnings that considerably exceed analysts’ expectations and markets are expected to react favorably. Since ranking institutions include the return on the day of the recommendation revision, analysts following firm ‘A’ can enhance their perceived stock-picking performance by issuing an upgrade later during the same day that the favorable earnings news is released to the public.

Analysts with poor past recommendation profitability are likely to have greater incentives to strategically time their recommendations. This is because analysts with poor past stock-picking performance are in greater need of improving their performance than other analysts who have superior track records. Not all analysts are likely to strategically time their recommendations equally due to reputational costs associated with excessive piggybacking on earnings. In order to examine whether analysts issue recommendation revisions strategically, I test the following hypothesis which predicts that analysts’ timing is a function of their past stock-picking performance.

H8. Analysts with poorer past stock picking performance are more likely to revise their recommendations in line with recent earnings surprises.

4.4 Contradictory information

An additional factor that is likely to affect an analyst’s reaction to earnings announcements is the contradictory/confirmatory nature of earnings surprises. Earnings announcements can reveal information that is consistent or inconsistent with the analysts’ prior opinion of the firm. For instance, a positive earnings surprise released by a firm that the analyst had an unfavorable (sell or strong sell) recommendation rating constitutes contradictory information whereas a positive earnings surprise released by a firm with a favorable (buy or strong buy) recommendation rating constitutes confirmatory information.

An interesting question is how analysts react to the arrival of contradictory versus confirmatory information. On the one hand, Bayesian theory posits that analysts would update their opinions in light of new evidence regardless of whether the new evidence contradicts or confirms analysts' prior beliefs. On the other hand, the confirmation bias hypothesis grounded in behavioral theory (Lord et al. 1979) predicts that analysts would weigh confirming evidence more heavily than contradictory evidence.

The two theories explaining possible behavior of individuals provide a wide spectrum in which analysts' behavior may take place. It is unclear, ex-ante, which end of the spectrum analysts' behavior more closely aligns with. Therefore, I empirically test the following non-directional hypothesis which intends to improve our understanding of how analysts handle and respond to contradictory information.

H9. Analysts place equal weight on earnings surprises that contradict or confirm their prior recommendation ratings.

4.5 Empirical analysis

4.5.1 Methodology

The equation below is estimated using ordered logistic regression to examine the relation between recommendation revisions and earnings surprises and how this relation varies in relation to expectation management, analysts' prior stock picking performance and the contradictory/confirmatory nature of the earnings news.

$$\begin{aligned} \Delta REC_{ita} = {} & \alpha + \beta_1 STRONG\_BUY_{ita} + \beta_2 BUY_{ita} + \beta_3 SELL_{ita} + \beta_4 STRONG\_SELL_{ita} + \beta_5 LOSS_{it} \\ & + \beta_6 SPECIAL_{it} + \beta_7 SUE_{it} + \beta_8 FE_{ita} + SUE_{it} \times (\beta_9 EXP\_MGMT_{it} + \beta_{10} PERF_{ita} \\ & + \beta_{11} CONTRADICT_{ita}) + \varepsilon_{ita}, \end{aligned} \tag{2}$$

ΔREC_{ita} = The change in recommendation rating issued by analyst *a*, for firm *i*, within three days of fiscal quarter *t*'s earnings announcement. Revisions are coded into five categories: (1) Strong Upgrade; a multiple level increase in the recommendation rating, (2) Upgrade; a single level increase in the recommendation rating, (3) No Revision; no change in the recommendation rating, (4) Downgrade; a single level decrease in the recommendation rating, (5) Strong Downgrade; a multiple level decrease in the recommendation rating.

$STRONG\_BUY_{ita}$	=	An indicator variable that takes a value of one for analysts who had a strong buy recommendation rating prior to firm *i*'s fiscal quarter *t* earnings announcement.
BUY_{ita}	=	An indicator variable that takes a value of one for analysts who had a buy recommendation rating prior to firm *i*'s fiscal quarter *t* earnings announcement.
$SELL_{ita}$	=	An indicator variable that takes a value of one for analysts who had a sell recommendation rating prior to firm *i*'s fiscal quarter *t* earnings announcement.
$STRONG\_SELL_{ita}$	=	An indicator variable that takes a value of one for analysts who had a strong sell recommendation rating prior to firm *i*'s fiscal quarter *t* earnings announcement.
$LOSS_{it}$	=	An indicator variable equal to one for firm-quarters with negative income before extraordinary items.
$SPECIAL_{it}$	=	An indicator variable that takes a value of one for firm-quarters with negative special items and zero otherwise.
SUE_{it}	=	Reported earnings minus the median analyst earnings forecast for firm *i* fiscal quarter *t* divided by the share price at previous fiscal quarter's end-date.
FE_{it}	=	Reported earnings minus analyst *a*'s last earnings forecast for firm *i* fiscal quarter *t* divided by the share price at previous fiscal quarter's end-date.
EXP_MGMT_{it}	=	An indicator variable that equals one for firms that met or exceeded final consensus earnings expectations but missed the earnings expectations at the beginning of the fiscal quarter.
$PERF_{ita}$	=	An indicator variable that equals one for analysts with stock picking performance that exceed at least half of the analysts covering the same industry as of the day before firm *i*'s fiscal quarter *t* earnings announcement date. Stock picking performance is measured within each industry (two-digit SIC) on a daily basis as the running cumulative average return associated with recommendations of each analyst.
$CONTRADICT_{ita}$	=	An indicator variable that takes a value of one when a firm that the analyst has a strong buy or buy recommendation rating misses the earnings expectations or when a firm that the analyst has a sell or strong sell recommendation rating meets or exceeds the earnings expectations.

The dependent variable, ΔREC_{ita}, is the recommendation revision issued by analyst *a* within three days (0, +2) after firm *i*'s fiscal quarter *t* earnings announcement. It consists of five categories; (1) Strong Downgrade, (2) Downgrade, (3) No Revision, (4) Upgrade and (5) Strong Upgrade and indicates the direction and magnitude of the recommendation revision. For example, a revision from Hold to Buy is coded as an Upgrade whereas a revision from Hold to Strong Buy is coded as a Strong Upgrade. The change in recommendation rating is expected to be a function of the prior recommendation rating because the more favorable the past rating is the less room there is for the analyst to upgrade the rating further and vice versa. Therefore, the equation above includes four dummy variables (*STRONG_BUY, BUY*, *SELL* and *STRONG_SELL*) that control for analyst *a*'s recommendation rating prior to firm *i*'s fiscal quarter *t* earnings announcement. The dummy variable *HOLD* is excluded to avoid perfect multicollinearity. The *LOSS* and *SPECIAL* variables are included to control for firm-quarters that had negative net income before extraordinary items and firms that reported negative special items. Analysts are expected to react negatively to firms that report negative earnings or negative special items. Finally, a key factor that is expected to influence analysts' recommendation revision after the earnings announcement is the earnings surprise. In order to capture this factor, the standardized unexpected earnings (*SUE*) variable is included in the equation above.

The empirical model above examines the variation in the emphasis that analysts place on earnings surprises with respect to expectation management, past stock picking performance and the contradictory/confirmatory nature of the earnings surprise. Firm-quarters with high-likelihoods of expectation management are identified as fiscal quarters where the reported earnings fell short of initial earnings expectations but met or exceeded the final earnings expectations (Bartov et al.2002). These firms are more likely to have achieved earnings expectations through expectation management because without a reduction in the early quarter earnings forecasts they would have missed the final earnings expectations. Therefore, the empirical model employs the interaction of *SUE* with *EXP_MGMT*. The interaction variable *SUE×EXP_MGMT* tests whether the relation between changes in recommendations (*ΔREC*) and earnings surprises (*SUE*) is significantly different when there is a high likelihood of expectation management. A negative coefficient on the interaction variable, *SUE×EXP_MGMT* is expected if analysts discount the quality of earnings surprises because of the presence of expectation management activity.

Further, analysts with poor past stock-picking performance, in order to improve the perceived profitability of their recommendations, are more likely to revise their recommendations after earnings announcements in line with earnings surprises. To the extent that this influences analysts' decisions, I expect a stronger relation between recommendation changes (*ΔREC*) and earnings surprises (*SUE*) for analysts with inferior past stock-picking performance. In order to empirically test this hypothesis, the model above includes the variable *PERF. PERF* is an indicator variable that equals one for analysts with recommendation profitability that exceeds at least 50 percent of the other analysts covering the same industry. Analysts' stock picking performance is computed on a daily basis for each analyst and industry (two-digit SIC code) pair. In order to measure the stock picking performance, I compute the returns to analysts' recommendations beginning on the day that the recommendation was issued. Similar to *Wall Street Journal's* methodology, returns associated with Strong Buy and Buy recommendation ratings are multiplied by one and returns associated with Sell and Strong Sell recommendation ratings are multiplied by negative one. The returns to the recommendations are cumulated over the calendar year starting from the day of the recommendation date until the next recommendation date. If an analyst does not issue a recommendation revision within the next six month period the position is liquidated. Using the running cumulative returns, I rank analysts on a daily basis within each industry. $PERF_{ita}$ equals one when the percentage of analysts covering the same industry that analyst *a* outperformed as of the day before firm *i's* fiscal quarter *t* earnings announcement date is greater than 0.50. The coefficient of the interaction variable, $SUE_{it} \times PERF_{ita}$, tests whether analysts place more weight on earnings surprises when their stock picking performance lags their peers' performance. Since *PERF* increases as the relative performance of the analyst increases, I expect the coefficient of the interaction variable to be negative.

Finally, the variable $CONTRADICT_{ita}$ is a dummy variable that takes a value of one when firm *i's* fiscal quarter *t* earnings announcement contradicts analyst *a*'s prior recommendation rating (e.g. the firm reports a positive earnings surprise when the analyst has an unfavorable rating). The coefficient of the interaction variable $SUE_{it}\times CONTRADICT_{ita}$ tests whether analysts place more weight on earnings surprises when they receive contradictory information.

The dependent variable consists of five categories that range from unfavorable to favorable where differences between categories are unknown. Therefore, I employ an ordered logistic regression to estimate the equation. In order to account for possible correlation across residuals within the same firm I use firm-clustered standard errors to test the statistical significance of coefficients.[2]

4.5.2 Results

Table 6 reports sample summary statistics and the estimation of the ordered logistic regression. The descriptive statistics provided in Panel A indicate that the average recommendation revision is equal to zero and the mean prior recommendation rating is 2.362 (between Buy and Hold). Roughly 18 percent of the observations in the sample are loss firms and 31 percent report negative special items. Both forecast errors and standardized unexpected earnings are on average equal to zero. Finally, 30 percent of the analyst-firm-quarter observations are likely to have expectation management, 52 percent of the sample is comprised of observations from analysts in the top 50 percentile and 23 percent of the observations involve contradictory information. The correlation matrix presented in Panel B suggests that correlations among independent variables are in general low. One exception is the high correlation between analysts' forecast errors (*FE*) and standardized unexpected earnings (*SUE*). Since standardized unexpected earnings are based on consensus expectations computed using individual earnings forecasts the two variables are highly correlated.

[2] In untabulated analyses, I re-estimate equation (2) using a sample of analyst-firm-quarter observations with interior recommendation ratings (buy, hold and sell) and find similar results.

The first model reported in Table 6 Panel C involves the regression of *ΔREC* on control variables (*STRONG_BUY, BUY, SELL, STRONG_SELL, LOSS* and *SPECIAL*), the analyst's forecast error (*FE*) and the earnings surprise (*SUE*). In Model 1, the coefficients of *STRONG_BUY* and *BUY* are estimated to be -1.983 and -1.336 and are both statistically significant (p<0.01). The coefficients of *SELL* and *STRONG_SELL* are estimated to be 0.737 and 1.171 and statistically significant (p<0.01). The coefficients of the four prior recommendation rating indicator variables indicate that the more favorable (unfavorable) the prior recommendation rating is, the less likely it is for the analyst to upgrade (downgrade) the previous recommendation rating. The coefficient of the *LOSS* variable is estimated to be -0.170 (p<0.01) and indicates that for loss firms, analysts are 16.4 percent more likely to downgrade their recommendation ratings. The coefficient of the variable *SPECIAL* is not estimated to be statistically significant. This suggests that there is no association between recommendation revisions and special items.

Table 6, Model 1 also reports the estimated coefficients of analysts' forecast error (*FE*) and standardized unexpected earnings (*SUE*). The forecast error (*FE*) variable is estimated to have a coefficient of 10.035 (p<0.01) and indicates a 7.7 percent increase in the probability of an upgrade associated per one-standard deviation increase in *FE*. The standardized unexpected earnings (*SUE*) variable is estimated to have a coefficient of 20.925 (p<0.01) and corresponds to a 12.1 percent increase in the probability of an upgrade revision per one standard deviation increase in *SUE*. The two variables suggest that analysts place significant emphasis on both their own forecasts and the consensus expectations when revising their recommendations after earnings announcements. However, the Chi-Square value and the associated p-value of the Wald test of equality of the two coefficients reported in Table 6 indicates that the coefficient of the *SUE* variable is significantly greater than the coefficient of the *FE* variable. The statistically significant difference between *SUE* and *FE* suggests that analysts place significantly greater emphasis on the consensus earnings expectations than on their own forecasts to value companies and issue recommendation revisions. I re-estimate Model 1 excluding the *FE* variable. The column labeled Model 2 reports the estimation results. In Model 2 the coefficient of the *SUE* variable indicates that the probability of an upgrade increases 17.5 percent per one-standard deviation increase in the earnings surprise.

Bartov et al. (2002) discuss and examine the possibility of managers achieving earnings expectations by dampening analysts' earnings forecasts. They show that firms that are likely to have achieved earnings targets by managing earnings expectations are also rewarded by investors. I test whether analysts recognize the presence of expectation management and react differently to earnings surprises when earnings targets are likely to have been achieved via expectation management. Consistent with Bartov et al. (2002), I construct an indicator variable which takes a value of one for firms that reported earnings that missed early quarter consensus expectations but exceeded the most recent consensus expectation before the earnings announcement. Model 3, includes *SUE×EXP_MGMT* which is the interaction of unexpected earnings (*SUE*) and the expectation management (*EXP_MGMT*) variables. The *SUE×EXP_MGMT* interaction variable tests whether analysts react differently to earnings surprises when managers are likely to have managed earnings expectations. The interaction variable is estimated to be -20.732 (p<0.01) and suggests that analysts assign significantly less weight (64.6 percent) to earnings surprises when expectations are likely to have been achieved via expectation management.

Altinkilic and Hansen (2009) find that analysts' recommendation revisions often follow important corporate events. They further propose the possibility of analysts strategically piggybacking on earnings surprises to enhance their stock picking performance with the goal of improving the perceived profitability of their recommendations. This paper builds upon Altinkilic and Hansen's (2009) work by empirically testing whether analysts strategically time their revisions to enhance their perceived stock performance. If stock picking performance is a key factor that motivates analysts to time their revisions after recent news, analysts with poorer stock picking performance are more likely to piggyback on recent news as they are in greater need of improving their track records. Model 4 includes the interaction of analyst's past stock picking performance (*PERF*) and standardized unexpected earnings (*SUE*). The *PERF* variable equals one for analysts with superior stock picking performance and lower for analysts with poorer stock picking performance. To the extent that analysts with poorer stock picking performance piggyback more frequently following recent news, I expect the coefficient of the interaction variable (*SUE×PERF*) to be significantly negative. In Model 4, the coefficient of *SUE×PERF* is estimated to be -5.587 (p=0.02) and indicates that analysts within the top 50 percentile based on performance react 16 percent less strongly to earnings surprises than other analysts. The negative *SUE×PERF* empirically supports Altinkilic and Hansen's (2009) explanation that the tendency of recommendations to cluster after news is partly driven by analysts' intentions to improve their perceived performance.

Finally, I examine whether analysts place greater emphasis on earnings when they contradict their prior recommendation ratings. Bayesian theory posits that individuals, upon receiving new information update their opinions independent of whether the new information is contradictory or confirmatory. Conversely, the confirmation bias hypothesis predicts that analysts would weigh confirming evidence more heavily. Model 5 tests this hypothesis by including the *CONTRADICT* indicator variable that takes a value of one for analysts who had a favorable (unfavorable) recommendation on a firm but observed a negative (positive) earnings surprise and zero otherwise. In Model 5, the interaction of the *SUE* and *CONTRADICT* variables is estimated to be 6.993 (p<0.01) and indicates that analysts react more strongly to earnings surprises when they contradict analysts' prior recommendation rating. The positive coefficient on *SUE×CONTRADICT* suggests that analysts do not appear to give less weight to conflicting information as the confirmation hypothesis predicts. In contrast, analysts appear to react more strongly to earnings information when it contradicts their prior opinion of the firm.

In conclusion, several insights emerge from the analyst-firm-quarter level analysis conducted in this section. First, when valuing companies analysts appear to rely more on consensus expectations than their own forecasts. Analysts react less strongly to earnings surprises when managers are likely to have achieved earnings targets by manipulating expectations. Analysts with poorer past recommendation profitability are more likely to react to earnings surprises. Finally, in contrast to the confirmation bias hypothesis, analysts do not appear to assign less weight to contradictory earnings information.

5. Timing of recommendation revisions and the pricing of earnings information

This section examines whether recommendation revisions issued shortly after earnings announcements improve the extent to which earnings information is incorporated into share prices. Analysts, by interpreting public disclosures and communicating their interpretations to investors on a timely basis, can potentially help markets more efficiently incorporate earnings information into share prices. Zhang (2008) finds that earnings announcements coupled with at least one earnings forecast are associated with higher earnings response coefficients and exhibit smaller post-earnings-announcement returns than firms without forecasts following earnings announcements. Zhang (2008) concludes that analysts' responsiveness contributes to a more efficient processing of earnings information.

In addition to forecasts, recommendations constitute an alternative way through which analysts can respond to earnings announcements and communicate their interpretations of the earnings disclosure. Different from forecasts, recommendations are intended to reveal analysts' opinion of the current firm valuation whereas forecasts provide analysts' estimate of next period earnings. In this sense, recommendations can be interpreted as analysts stating that they evaluated the new earnings disclosure and the market's response to it and conclude that the firm is misvalued. To the extent that recommendation revisions provide a more direct and easily applicable signal to investors, I expect recommendation revisions to contribute more to the pricing of earnings information than forecasts that are issued after earnings announcements.

H10. Earnings announcements coupled with recommendation revisions exhibit higher earnings response coefficients than earnings announcements coupled with earnings forecasts.

The relation between analysts' recommendation responsiveness and the post-earnings announcement drift is less clear. On the one hand, analysts' recommendation revisions are likely to reveal analysts' private information and help market participants incorporate earnings information more effectively. On the other hand, analysts are likely to identify firms and issue recommendation revisions following earnings announcements only when they detect mispricing that is beyond a minimum threshold. This motivation is likely to concentrate recommendations after earnings announcements for firm-quarters with greater post-earnings announcement drift potential. This effect would facilitate a positive association between recommendation revisions and the post-earnings announcement drift. It is unclear which effect dominates the relation between the post-earnings announcement concentration of recommendations and the post-earnings announcement drift. Therefore, I test the following non-directional hypothesis.

H11. There is no association between the timing of recommendation revisions after earnings announcements and the drift that follows.

5.1 Methodology

This section employs a methodology that is similar to the one used by Zhang (2008) in order to be consistent with the prior literature and also to allow for a comparison of the effect of analyst responsiveness based on recommendations and forecasts. I measure the market reaction to earnings announcements as the three day (-1, +1) cumulative size-adjusted return (*CAR (-1,+1)*) and compute the post earnings announcement drift (*PEAD*) as the size-adjusted buy and hold return commencing two days after the current earnings announcement date and ending one day after the next quarter's earnings announcement date. I estimate the following model to examine how analysts' responsiveness, based on recommendation revisions and forecasts, affects the extent to which share prices reflect earnings information on the announcement date:

$$CAR\,(-1,+1)_{it} = \alpha + \beta_1 SUE_{it} + \beta_2 RRESP_{it} + \beta_3 FRESP_{it} + \beta_4 SUE{\times}RRESP_{it} + \beta_5 SUE{\times}FRESP_{it} \tag{3}$$

$$+ SUE_{it} \times (\beta_6 LOGMV_{it} + \beta_6 MERGER_{it} + \beta_7 SPECIAL_{it} + \beta_8 Q4_{it} + \beta_9 NEGSURP_{it}$$

$$+ \beta_{10} EXP_{it} + \beta_{11} BSIZE_{it} + \beta_{12} COV_{it} + \beta_{13} INST_{it}) + \beta_{14} LOGMV_{it} + \beta_{15} MERGER_{it}$$

$$+ \beta_{16} SPECIAL_{it} + \beta_{17} Q4_{it} + \beta_{18} NEGSURP_{it} + \beta_{19} EXP_{it} + \beta_{20} BSIZE_{it} + \beta_{21} COV_{it}$$

$$+ \beta_{22} INST_{it} + \varepsilon_{it},$$

$CAR\,(-1,+1)_{it}$	=	Cumulative size-adjusted returns for the three-day period centered on firm *i's* fiscal quarter *t* earnings announcement date.
SUE_{it}	=	Unexpected earnings scaled by share price as of the end of the previous fiscal quarter.
$FRESP_{it}$	=	An indicator variable that equals one for firm-quarters that had at least one analyst who issued a new forecast on the earnings announcement day or the day after (0, 1).
$RRESP_{it}$	=	An indicator variable that equals one for firm-quarters that had at least one analyst who revised his/her recommendation rating on the earnings announcement day or the day after (0, 1).
$LOGMV_{it}$	=	Natural logarithm of the firm's market capitalization as of the fiscal quarter end date.
$MERGER_{it}$	=	An indicator variable that equals one if the firm was involved in a merger or acquisition and zero otherwise.
$SPECIAL_{it}$	=	An indicator variable that equals one if the firm reported negative special items and zero otherwise.
$Q4_{it}$	=	An indicator variable that takes a value of one for the fourth fiscal quarters and zero otherwise
$NEGSURP_{it}$	=	An indicator variable that equals one if the firm missed earnings expectations and zero otherwise.
EXP_{it}	=	Median firm-specific experience of analysts following firm *i* during fiscal quarter *t.*
$BSIZE_{it}$	=	Median size of the brokerage house that employs analysts that covered firm *i* during fiscal quarter *t.* Brokerage house size is measured as the number of analysts that the brokerage house employs.
COV_{it}	=	Number of analysts who issued earnings forecasts for firm *i*'s fiscal quarter *t* earnings.
$INST_{it}$	=	The percentage of shares held by institutional investors as of the most recent calendar quarter prior to the fiscal quarter end-date.

In equation (3) above, the coefficient of *SUE*, β_1, measures the extent to which share prices reacted to earnings surprises during the three day period, centered on the earnings announcement date. The interaction of the unexpected earnings variable (*SUE*) with the analyst responsiveness dummy variable based on earnings forecasts (*FRESP*) provides an estimate of the incremental market reaction to earnings surprises for firm-quarters in which at least one analyst issued an earnings forecast during the two day period after the earnings announcement (0,1). Similarly, the coefficient of the interaction variable, *UE×RRESP,* measures the incremental market reaction to earnings announcements coupled with at least one recommendation revision during days 0 and 1 relative to earnings announcement dates. The remaining variables and their interactions with unexpected earnings are intended to control for confounding factors that may affect the market reaction to earnings announcements.

In addition, I estimate the empirical model below to examine the relation between the post-earnings announcement drift and analyst responsiveness based on earnings forecasts and recommendations:

$$\begin{aligned} PEAD_{it} = {} & \alpha + \beta_1 DUE_{it} + \beta_2 RRESP_{it} + \beta_3 FRESP_{it} + \beta_4 DUE{\times}RRESP_{it} + \beta_5 DUE{\times}FRESP_{it} \\ & + DUE_{it} \times (\beta_6 LOGMV_{it} + \beta_6 MERGER_{it} + \beta_7 SPECIAL_{it} + \beta_8 Q4_{it} + \beta_9 NEGSURP_{it} + \beta_{10} EXP_{it} \\ & + \beta_{11} BSIZE_{it} + \beta_{12} COV_{it} + \beta_{13} INST_{it}) + \beta_{14} LOGMV_{it} + \beta_{15} MERGER_{it} + \beta_{16} SPECIAL_{it} \\ & + \beta_{17} Q4_{it} + \beta_{18} NEGSURP_{it} + \beta_{19} EXP_{it} + \beta_{20} BSIZE_{it} + \beta_{21} COV_{it} + \beta_{22} INST_{it} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where $PEAD_{it}$ is the size-adjusted buy and hold return for the period beginning two days after the current quarter's earnings announcement date and ending one day after the next quarter's earnings announcement date. *DUE* is the decile ranking of the earnings surprise minus one and divided by nine. The remaining variables are as defined in equation (3).

In equation (4), the coefficient of the decile ranking of the unexpected earnings provides an estimate of the return differential between firms that were in the top and bottom earnings surprise deciles. The coefficient of the interaction variable *DUE×RRESP* (*DUE×FRESP*) tests whether the post-earnings announcement drift is more or less pronounced for firms with or without recommendations (forecasts). The remaining variables control for other confounding factors that may influence the degree of the post-earnings announcement drift.[3]

5.2 Results

Table 7, Models 1 and 2 present the estimation results of equation (3). In Model 1, consistent with the prior literature, the coefficient of unexpected earnings (also commonly referred to as the earnings response coefficient) is estimated to be positive and statistically significant (1.710; *p*-value<0.01). The positive coefficient of unexpected earnings suggests that the direction and magnitude of the market reaction is aligned with the earnings surprise. The coefficient of the interaction variable *SUE× FRESP* is estimated to be 1.265 (p<0.01) and confirms Zhang's (2008) finding that the strength of the market reaction to earnings surprises is higher for firms that have at least one analyst who issued a forecast within two days after the earnings announcement date. The coefficient of the interaction variable *SUE×RRESP* is estimated to be 2.713 (p<0.01) and suggests that market prices react more strongly to earnings when the earnings announcement is coupled with at least one recommendation revision within the two-day period after the earnings announcements. This finding suggests that the information released in recommendation revisions helps market participants better interpret earnings information and incorporate it into prices. I test whether the coefficients of *SUE×RRESP* (β_3) and *SUE×FRESP* (β_5) are equal. The F-statistics of the Wald test is equal to 92.684(p<0.01) and indicates that β_3 and β_5 are significantly different. This result suggests that earnings announcements coupled with recommendation revisions exhibit higher earnings response coefficients than announcements that are coupled with forecasts. Model 2 includes additional variables and their interactions with unexpected earnings to control for confounding factors. The results are similar. Unexpected earnings (*SUE*) and the earnings

[3] Following Zhang 2008, I delete observations with absolute studentized residuals greater than 2.

announcement market reaction (*CAR (-1, +1)*) are positively associated. The association between *SUE* and *CAR (-1, +1)* is stronger for earnings announcements with at least one analyst issuing an earnings forecast during the two days following earnings announcements (*SUE×FRESP)* and for announcements with at least one analyst issuing a revised recommendation (*SUE×RRESP*). The difference between the coefficients of *SUE×FRESP* and *SUE×RRESP* is also statistically significant in Model 2. In summary, the estimation results support the conclusion that analyst responsiveness, based on either earnings forecasts or recommendations, improve the extent to which earnings information is incorporated into prices. However, recommendation revisions appear to be associated with a significantly greater impact on earnings response coefficients than earnings forecasts.

Next, I examine whether analyst responsiveness in terms of recommendation revisions is associated with higher or lower post-earnings announcement returns. On the one hand, the information revealed by analysts via their recommendation revisions is found to increase the reaction on announcement dates. This is likely to reduce the post-earnings-announcement drift. On the other hand, analysts are more likely to revise their recommendations on earnings announcements for firm-quarters in which share prices are more misvalued. Further, market participants may discount the information communicated by analysts and only partially incorporate it to share prices. It is therefore unclear whether earnings announcements with recommendation revisions will precede higher or lower post-earnings announcement returns.

Model 3 reports the estimation results of the regression of post-earnings announcement returns (*PEAD*) on the unexpected earnings decile ranking (*DUE*) and its interaction with analyst responsiveness based on earnings forecasts (*FRESP*) and recommendation revisions (*RRESP*). The coefficient of the unexpected earnings surprise decile ranking (*DUE*) is estimated to be 0.072 ($p<0.01$). The *DUE* coefficient indicates that firms in the top earnings surprise decile outperformed firms in the bottom earnings surprise by 7.2 percent, controlling for analyst responsiveness. The interaction between *DUE* and analyst responsiveness based on earnings forecasts (*FRESP*) is estimated to be -0.035 ($p<0.01$). This supports the findings documented by Zhang (2008) and suggests that the post-earnings announcement drift is smaller in magnitude for earnings announcements with at least one analyst issuing an earnings forecast. This is consistent with analyst responsiveness facilitating a more efficient incorporation of earnings information to prices. Conversely, the coefficient of the interaction variable *DUE×RRESP* is estimated to be 0.015 ($p<0.01$). The positive *DUE×RRESP* coefficient indicates that the post-earnings announcement drift is larger in magnitude for firm-quarters with earnings announcements that were coupled with at least one recommendation revision. This result is consistent with analysts successfully identifying mispriced securities and investors failing to fully incorporate the information revealed in analysts' recommendation revisions. Model 4, repeats the same analysis with the inclusion of control variables. The results are qualitatively similar. The coefficient of the interaction variable, *DUE×FRESP,* is estimated to be negative (-0.022) whereas the coefficient of the variable *DUE×FRESP* is estimated to be positive (0.019). These results largely reaffirm the earlier inferences.

Overall, the empirical findings support the conclusion that the dissemination of recommendation revisions and earnings forecasts on earnings announcements facilitates a more efficient pricing of earnings information. Interestingly, the post-earnings announcement drift is found to be higher for firms with recommendation revisions issued shortly after earnings announcements and lower for firms with earnings forecasts. These results are consistent with analysts identifying cases where there are likely to be greater post-earnings announcement returns while investors fail to fully incorporate the information conveyed in analysts' recommendation revisions.

6. Conclusions

Financial analysts frequently recommend that their clients trade shortly after earnings announcements. I examine why analysts issue new recommendations based on information conveyed in earnings announcements which are expected to have already been incorporated into share prices. The empirical results suggest that analysts' are more likely to revise their ratings after earnings announcements for firms with larger earnings surprises, less information availability, more complex information and more informative earnings. Overall, the results support the conclusion that analysts revise their recommendations in reaction to earnings announcement when they perceive their information processing skills to be superior and when they have less information from sources other than earnings announcements.

In addition, this study reveals several key insights about how analysts use information from earnings announcements. First, analysts appear to assign greater weight to the consensus earnings expectations than to their own earnings forecast. Analysts seem to recognize expectation management activities and react less strongly to earnings surprises when managers are likely to have manipulated expectations to achieve non-negative earnings surprises. Further, analysts' decisions to revise their recommendations in reaction to earnings announcements appear to be partly driven by their concerns to improve their perceived stock-picking performance. Finally, in contrast to the confirmation bias hypothesis, analysts do not react less strongly to contradictory information signals. Overall, the empirical results provided in this study contribute to our understanding of the timing and determinants of analysts' recommendation revisions. The results highlight public information processing as an important driver of analysts' decision to issue new recommendations.

Finally, the examination of the relation between the pricing of earnings and analyst recommendation responsiveness suggests that analysts contribute to market efficiency. The results show that earnings announcements coupled with recommendation revisions are associated with significantly higher earnings response coefficients. This finding is consistent with analysts contributing to the efficiency in which markets incorporate earnings information. Further, a positive relation between analyst responsiveness and post-earnings-announcement returns is documented. This result suggests that not all of the information communicated by analysts is incorporated to prices on earnings announcements and that some of the information is impounded into share prices during the following three-month period.

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Table 1
Sample Composition
This table reports the industry and year breakdown of the final sample. The final sample consists of 88,797 firm-quarter observations corresponding to the intersection of Compustat, CRSP, I/B/E/S and CDA/Spectrum databases for the period 1994Q1 – 2010Q4. Panel A reports the number of observations per industry and Panel B provides a year-by-year breakdown of the sample.

Panel A: Industry Composition

Industry Name	Count	Industry Name	Count
Agriculture	152	Defense	145
Food Products	1395	Precious Metals	212
Candy & Soda	142	Non-Metallic and Ind. Metal Mining	336
Beer & Liquor	261	Coal	180
Tobacco Products	124	Petroleum and Natural Gas	4247
Recreation	434	Utilities	3411
Entertainment	1241	Communication	2564
Printing and Publishing	781	Personal Services	954
Consumer Goods	1285	Business Services	3787
Apparel	1084	Computer Hardware	2542
Healthcare	1580	Computer Software	6800
Medical Equipment	2433	Electronic Equipment	5865
Pharmaceutical Products	4169	Measuring and Control Equipment	1654
Chemicals	2020	Business Supplies	1240
Rubber and Plastic Products	416	Shipping Containers	326
Textiles	363	Transportation	2594
Construction Materials	1175	Wholesale	2431
Construction	1079	Retail	6170
Steel Works Etc	1337	Restaurants, Hotels, Motels	1622
Fabricated Products	145	Banking	7838
Machinery	2988	Insurance	3510
Electrical Equipment	1014	Real Estate	90
Automobiles and Trucks	1397	Trading	1922
Aircraft	410	Other	783
Shipbuilding, Railroad Equipment	149	*Total*	88797

Panel B: Number of observations per year

Fiscal Year	Count	Fiscal Year	Count
1994	3668	2003	6057
1995	4364	2004	5842
1996	4620	2005	5700
1997	4741	2006	5665
1998	5241	2007	5610
1999	5131	2008	5648
2000	4574	2009	5670
2001	4628	2010	5361
2002	6277	*Total*	88797

Table 2
Descriptive Statistics
This table presents the descriptive statistics of the sample used in sections 3 and 5. The first column reports the variable name followed by mean, 1st quartile, median, 3rd quartile and standard deviation values for each variable. All continuous variables, excluding *LOGMV* and *LOGSEGMENT*, are winsorized at the bottom and top one percent.

	Mean	1st Quartile	Median	3rd Quartile	Std. Dev.
REVCONC	0.231	0.000	0.000	0.500	0.358
|SUE|	0.009	0.000	0.001	0.004	0.160
FD	0.650	0.000	1.000	1.000	0.477
MV (in $ millions)	4955.440	396.995	1177.817	3948.079	10023.122
LOGMV	7.180	5.984	7.071	8.281	1.721
COV	9.641	5.000	8.000	13.000	6.462
AGE	19.440	7.000	13.000	27.000	17.557
SEGMENT	2.172	1.000	1.000	3.000	1.684
LOGSEGMENT	0.531	0.000	0.000	1.099	0.681
R&D	0.057	0.000	0.000	0.053	0.127
B/M	0.517	0.263	0.441	0.688	0.350
MERGER	0.144	0.000	0.000	0.000	0.351
SPECIAL	0.289	0.000	0.000	1.000	0.453
NEGSURP	0.296	0.000	0.000	1.000	0.456
ERC	9.559	0.452	3.436	11.774	16.517
INST	0.615	0.452	0.648	0.806	0.251
LOSS	0.206	0.000	0.000	0.000	0.404
CAR(-1, +1)	0.000	-0.039	0.000	0.042	0.078
PEAD	-0.000	-0.115	-0.006	0.104	0.197
RRESP	0.300	0.000	0.000	1.000	0.458
FRESP	0.770	1.000	1.000	1.000	0.421
Q4	0.269	0.000	0.000	1.000	0.444
EXP	9.667	5.500	8.500	12.500	5.730
BSIZE	48.912	28.000	44.000	62.500	27.799
N	88797				

Table 3
Correlation Matrix
This table reports the Pearson correlations of the independent variables employed in the regression analysis. The first column indicates the variable number followed by the variable name. The conserve space only variable numbers are reported in the column headers.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1 *DSUE*	1																	
2 *FD*	0	1																
3 *LOGMV*	-0.28	0.07	1															
4 *COV*	-0.19	0.16	0.66	1														
5 *AGE*	-0.06	-0.01	0.46	0.16	1													
6 *LOGSEGMENT*	0	0.13	0.24	0.06	0.33	1												
7 *DRND*	0.02	0.02	-0.03	0.06	-0.02	0.03	1											
8 *B/M*	0.23	0.05	-0.2	-0.17	0.12	0.11	-0.25	1										
9 *MERGER*	-0.06	-0.01	-0.03	-0.02	-0.06	0.06	0.04	-0.05	1									
10 *SPECIAL*	0.03	0.18	0.09	0.12	0.03	0.09	0.12	0.04	0.04	1								
11 *NEGSURP*	0.24	-0.02	-0.16	-0.12	-0.02	-0.02	-0.04	0.09	-0.01	0.05	1							
12 *ERC*	-0.24	0.17	0.14	0.17	-0.02	0.01	0.06	-0.15	0.07	0.07	-0.07	1						
13 *INST*	-0.1	0.24	0.25	0.25	0.06	0.12	0.04	-0.07	0.1	0.09	-0.09	0.12	1					
14 *RRESP*	0	0.13	0.08	0.15	-0.02	0.01	0.08	-0.06	0.01	0.03	-0.01	0.07	0.07	1				
15 *FRESP*	-0.09	0.31	0.3	0.33	0.08	0.08	0.07	-0.07	0.01	0.07	-0.09	0.12	0.25	0.18	1			
16 *Q4*	0	0.04	-0.01	0.01	-0.01	-0.01	0	-0.01	0.01	0.1	0.02	0	-0.04	-0.01	0	1		
17 *EXP*	0.01	0.01	0.22	0.08	0.33	0.13	-0.04	0.17	-0.07	0.05	0	0.01	0.06	-0.01	0.05	-0.01	1	
18 *BSIZE*	-0.03	0.05	0.37	0.15	0.23	0.18	-0.1	0.04	0	0.08	-0.04	0.03	0.16	-0.01	0.11	-0.01	0.18	1

Table 4
Estimation Results
This table presents the generalized linear model estimation results of equation (1) which involves the regression of the concentration of recommendation revisions (*REVCONC*) on proxies for earnings surprise, information availability, information complexity, earnings informativeness and demand for advice. The independent variables are organized by categories of the factors that they intend to capture. The first column reports the variable names and the second column indicates the expected sign of each variable. The estimation results of models 1-5 are reported in the remaining columns. Z-statistics based on firm-clustered standard errors are reported in parentheses. *, ** and *** indicate statistical significance at ten, five, and one percent significance levels.

	Exp. sign	Model 1	Model 2	Model 3	Model 4	Model 5
Constant		-1.187***	-1.285***	-1.238***	-1.247***	-1.247***
		(-125.79)	(-29.99)	(-26.16)	(-26.49)	(-25.86)
Earnings Surprise (H1):						
DSUE	+	0.214***	0.158***	0.158***	0.183***	0.183***
		(9.29)	(6.62)	(6.37)	(7.31)	(7.30)
Information Availability (H2):						
FD	+		0.516***	0.534***	0.520***	0.520***
			(29.24)	(29.80)	(28.81)	(28.25)
LOGMV	-		-0.016**	-0.015*	-0.016**	-0.016**
			(-2.07)	(-1.89)	(-2.04)	(-2.01)
COV	-		-0.009***	-0.009***	-0.010***	-0.010***
			(-5.44)	(-5.89)	(-6.51)	(-6.50)
AGE	-		-0.004***	-0.004***	-0.003***	-0.003***
			(-6.46)	(-5.72)	(-5.59)	(-5.59)
Information Complexity (H3):						
LOGSEGMENT	+			0.023*	0.023*	0.023*
				(1.74)	(1.76)	(1.76)
DRND	+			0.214***	0.212***	0.212***
				(9.85)	(9.83)	(9.83)
B/M	-			-0.096***	-0.086***	-0.086***
				(-3.87)	(-3.50)	(-3.50)
MERGER	+			0.058***	0.051**	0.051**
				(2.87)	(2.50)	(2.50)
SPECIAL	+			-0.097***	-0.100***	-0.100***
				(-5.92)	(-6.09)	(-6.09)
NEGSURP	+			0.062***	0.061***	0.061***
				(3.88)	(3.82)	(3.82)
Earnings Informativeness (H4):						
ERC	+				0.003***	0.003***
					(6.77)	(6.77)
Demand for Advice (H5):						
INST	+					-0.002
						(-0.08)
Observations		88797	88797	88797	88797	88797
Chi-squared		86.37	980.12	1196.96	1246.45	1246.62
p-value		0.00	0.00	0.00	0.00	0.00

Table 5

Robustness Checks

This table presents the estimation results conducted to check for robustness. Columns 3-6 report results based on ordinary least squares (OLS), OLS with firm & fiscal quarter clustered standard errors, Fama and Macbeth (1973) and random-effects GLS estimation methods. The dependent variable in all models is the concentration of recommendation revisions after earnings announcements. Independent variables are organized by categories of the factors that they capture. The first column reports the variable names and the second column indicates the expected sign of each variable. *t*-statistics are reported in parentheses. *, ** and *** indicate statistical significance at ten, five, and one percent significance levels.

	Exp. Sign	OLS	Double Clustered Std. Errors	Fama & Macbeth	Random-Effects GLS
Constant		0.244***	0.244***	0.306***	0.204***
		(33.85)	(14.56)	(16.18)	(22.84)
Earnings surprise (H1):					
DSUE	+	0.027***	0.027***	0.024***	0.039***
		(6.60)	(5.68)	(5.40)	(8.76)
Information Availability (H2):					
FD	+	0.088***	0.088***		0.084***
		(32.94)	(9.28)		(27.31)
LOGMV	-	-0.005***	-0.005***	-0.007***	0.001
		(-4.27)	(-2.61)	(-4.29)	(0.85)
COV	-	-0.002***	-0.002***	-0.001***	-0.002***
		(-6.23)	(-4.64)	(-3.57)	(-6.50)
AGE	-	-0.001***	-0.001***	-0.000***	-0.001***
		(-6.47)	(-4.43)	(-4.52)	(-5.36)
Information Complexity (H3):					
LOGSEGMENT	+	0.003*	0.003	0.000	0.005**
		(1.73)	(1.27)	(0.10)	(2.00)
DRND	+	0.039***	0.039***	0.035***	0.038***
		(12.75)	(9.11)	(8.68)	(9.11)
B/M	-	-0.020***	-0.020***	-0.019***	-0.010**
		(-5.12)	(-4.21)	(-5.04)	(-2.16)
MERGER	+	0.009**	0.009**	0.010**	0.008**
		(2.48)	(2.13)	(2.38)	(2.26)
SPECIAL	+	-0.016***	-0.016***	-0.015***	-0.019***
		(-5.93)	(-5.18)	(-5.23)	(-6.61)
NEGSURP	+	0.010***	0.010***	0.012***	0.011***
		(3.67)	(2.96)	(3.79)	(3.96)
Earnings Informativeness (H4):					
ERC	+	0.001***	0.001***	0.001***	0.000***
		(8.91)	(7.29)	(8.79)	(4.19)
Demand for Advice (H5):					
INST	+	-0.003	-0.003	0.002	-0.001
		(-0.55)	(-0.29)	(0.20)	(-0.12)
Observations		88797	88797	88797	88797
R^2		0.021	0.021	0.014	0.020
Adjusted R^2		0.021	0.021		

Table 6

Earnings announcements and recommendation revisions

Panel A of this table reports descriptive statistics of the analyst-firm-quarter level sample. Panel B presents the correlation matrix among the variables and Panel C provides the ordered logistic regression results of equation (2). The empirical model involves the regression of recommendation revisions (*ΔREC*) on prior recommendation ratings, loss and special item dummy variables, forecast error and earnings surprise variables and the interaction of earnings surprise with expectation management, stock-picking performance and contradictory dummy variables. The first column reports the variable names and the second column indicates the expected sign of each variable. *z*-statistics based on firm-clustered standard errors are reported in parentheses. *, ** and *** indicate statistical significance at ten, five, and one percent significance levels.

Panel A: Descriptive Statistics

	Mean	1st Quartile	Median	3rd Quartile	Std. Dev.
REV	0.002	0.000	0.000	0.000	0.319
PRE_RATING	2.362	2.000	2.000	3.000	0.956
LOSS	0.184	0.000	0.000	0.000	0.387
SPECIAL	0.316	0.000	0.000	1.000	0.465
FE	-0.000	-0.000	0.000	0.002	0.008
SUE	0.000	0.000	0.000	0.001	0.006
EXP_MGMT	0.301	0.000	0.000	1.000	0.459
PERF	0.521	0.000	1.000	1.000	0.500
CONTRADICT	0.233	0.000	0.000	0.000	0.423
N	341903				

Panel B: Correlation Matrix

		1	2	3	4	5	6	7	8	9
1	*REV*	1.00								
2	*PRE_RATING*	0.18	1.00							
3	*LOSS*	-0.01	0.08	1.00						
4	*SPECIAL*	0.00	0.05	0.24	1.00					
5	*FE*	0.04	-0.03	-0.24	-0.05	1.00				
6	*SUE*	0.04	-0.03	-0.23	-0.05	0.85	1.00			
7	*EXP_MGMT*	0.00	0.04	0.03	0.03	0.07	0.12	1.00		
8	*PERF*	-0.00	-0.05	-0.02	-0.02	0.02	0.01	-0.03	1.00	
9	*CONTRADICT*	-0.07	-0.18	0.05	-0.01	-0.12	-0.14	-0.00	-0.02	1.00

Panel C:Ordered Logit Estimation Results

	Exp. sign	Model 1	Model 2	Model 3	Model 4	Model 5
STRONG_BUY	-	-1.983***	-1.947***	-1.951***	-1.951***	-1.939***
		(-77.17)	(-80.86)	(-81.12)	(-81.09)	(-79.52)
BUY	-	-1.336***	-1.329***	-1.332***	-1.331***	-1.320***
		(-47.90)	(-49.91)	(-50.06)	(-50.04)	(-48.93)
SELL	+	0.737***	0.735***	0.737***	0.737***	0.720***
		(21.88)	(23.11)	(23.19)	(23.17)	(22.24)
STRONG_SELL	+	1.171***	1.037***	1.040***	1.039***	1.023***
		(24.32)	(23.63)	(23.68)	(23.66)	(23.22)

LOSS	-	-0.170***	-0.175***	-0.154***	-0.154***	-0.150***
		(-6.38)	(-6.84)	(-5.90)	(-5.91)	(-5.75)
SPECIAL	-	-0.002	-0.003	-0.002	-0.002	-0.003
		(-0.10)	(-0.15)	(-0.11)	(-0.12)	(-0.16)
FE	+	10.035***				
		(5.01)				
SUE	+	20.925***	30.265***	32.080***	34.775***	31.285***
		(8.03)	(21.04)	(21.62)	(18.98)	(13.99)
SUE×EXP_MGMT	(H7) -			-20.732***	-20.742***	-19.487***
				(-3.88)	(-3.88)	(-3.64)
SUE×PERF	(H8) -				-5.587**	-5.231**
					(-2.28)	(-2.19)
SUE×CONTRADICT	(H9) ?					6.993***
						(2.62)
Cut1		-6.039***	-6.018***	-6.023***	-6.023***	-6.020***
		(-121.96)	(-141.18)	(-141.33)	(-141.35)	(-141.24)
Cut2		-4.960***	-4.923***	-4.928***	-4.928***	-4.925***
		(-105.17)	(-123.47)	(-123.67)	(-123.68)	(-123.64)
Cut3		3.024***	3.135***	3.132***	3.132***	3.132***
		(71.02)	(88.62)	(88.59)	(88.60)	(88.56)
Cut4		4.115***	4.225***	4.222***	4.222***	4.221***
		(90.90)	(109.90)	(109.92)	(109.92)	(109.87)
Year Dummies		Yes	Yes	Yes	Yes	Yes
Test of FE = SUE	(H6)	6.106(0.01)				
Test of SUE+SUE×EXP_MGMT=0				4.855(0.03)		
# of Observations		283050	341903	341903	341903	341903
Pseudo R-Squared		0.063	0.061	0.061	0.061	0.061
Wald Chi-Squared		9404.0	10071.0	10136.0	10142.3	10184.0
p-value		0.00	0.00	0.00	0.00	0.00

Table 7

Timing of recommendation revisions and the pricing of earnings information

This table reports the ordinary least squares estimation results of equation (3) and (4). The first two models involve the regression of market-adjusted earnings announcement returns (*CAR(-1, +1)*) on standardized unexpected earnings (*SUE*), recommendation revision dummy variable (*RRESP*), forecast dummy variable (*FRESP*) and control variables. Models 3 and 4 involve the regression of size-adjusted post-earnings announcement returns on the earnings surprise decile (*DUE*), recommendation revision dummy variable (*RRESP*), forecast dummy variable (*FRESP*) and control variables. Year fixed-effects are included in both models. The final four rows report F-statistics of the Wald test of the two interaction variable coefficients being equal, number of observations, R-square and adjusted R-square values, respectively. *t*-statistics based on firm clustered standard errors are reported in parentheses below the coefficient estimates. *, ** and *** indicate statistical significance at ten, five, and one percent significance levels.

	CAR (-1, +1)			*PEAD*	
	Model 1	Model 2		Model 3	Model 4
Constant	0.000	0.011***	*Constant*	-0.010***	-0.066***
	(0.38)	(6.94)		(-3.76)	(-14.71)
SUE	1.710***	3.187***	*DUE*	0.072***	0.209***
	(23.21)	(14.98)		(16.11)	(17.97)
RRESP	-0.008***	-0.007***	*RRESP*	-0.000	-0.001
	(-13.56)	(-12.03)		(-0.34)	(-0.43)
FRESP	0.001*	0.001	*FRESP*	0.003	-0.004**
	(1.86)	(0.98)		(1.43)	(-2.10)
SUE×RRESP	2.713***	2.743***	*DUE×RRESP*	0.015***	0.019***
	(25.20)	(26.68)		(3.28)	(4.00)
SUE×FRESP	1.265***	1.243***	*DUE×FRESP*	-0.035***	-0.022***
	(13.00)	(12.80)		(-6.87)	(-3.92)
LOGMV		-0.001***	*LOGMV*		0.005***
		(-4.91)			(9.23)
MERGER		0.001	*MERGER*		-0.001
		(1.55)			(-0.60)
SPECIAL		-0.001	*SPECIAL*		-0.004***
		(-0.99)			(-2.80)
Q4		0.001	*Q4*		0.026***
		(1.61)			(17.29)
NEGSURP		-0.035***	*NEGSURP*		-0.023***
		(-48.62)			(-4.87)

EXP		0.000	*EXP*		0.001***
		(1.44)			(4.95)
BSIZE		0.000	*BSIZE*		0.000*
		(1.62)			(1.95)
COV		0.000***	*COV*		-0.000
		(3.24)			(-1.07)
INST		0.002*	*INST*		0.012***
		(1.93)			(4.00)
SUE×LOGMV		-0.242***	*DUE×LOGMV*		-0.018***
		(-6.58)			(-9.49)
SUE×MERGER		0.579***	*DUE×MERGER*		0.002
		(4.13)			(0.39)
SUE×SPECIAL		0.130	*DUE×SPECIAL*		-0.012***
		(1.44)			(-2.59)
SUE×Q4		-0.738***	*DUE×Q4*		-0.014***
		(-8.09)			(-2.94)
SUE×NEGSURP		-2.153***	*DUE×NEGSURP*		-0.102***
		(-18.51)			(-7.94)
SUE×EXP		-0.011	*DUE×EXP*		-0.000
		(-1.52)			(-0.74)
SUE×BSIZE		-0.008***	*DUE×BSIZE*		0.000**
		(-5.40)			(2.02)
SUE×COV		-0.045***	*DUE×COV*		0.001**
		(-4.08)			(2.09)
SUE×INST		1.692***	*DUE×INST*		-0.023***
		(9.26)			(-2.65)
Year Dummies	Yes	Yes	Year Dummies	Yes	Yes
H0: *SUE×RRESP = SUE×FRESP*	92.684(0.00)	100.478(0.00)	H0: *DUE×RRESP = DUE×FRESP*	43.994(0.00)	26.853(0.00)
Number of Observations	86650	86777	Number of Observations	85033	85159
R-Square	0.110	0.146	R-Square	0.019	0.029
Adjusted R-Square	0.1	0.1	Adjusted R-Square	0.019	0.029