Do Analysts Strategically Employ Cash Flow Forecasts Revisions

to Offset Negative Earnings Forecasts Revisions?

CHOONG-YUEL YOO, *Korea Advanced Institute of Science and Technology (KAIST)*

JINHAN PAE, *Korea University*

Correspondence Address: Choong-Yuel Yoo. KAIST College of Business. 85 Hoegiro, Dongdaemoon-gu, Seoul, Korea. Phone: +82-2-958-3326 Fax: +82-2-958-3604 Email: cyoo@business.kaist.ac.kr

Acknowledgements: This paper is based on Choong-Yuel Yoo's dissertation, completed at Queen's University in Canada. Choong-Yuel is indebted to his advisors for their advice and encouragement and is grateful for generous research support provided by *ILJU* Foundation and Queen's University. We thank A. Rashad Abdel-Khalik, Dan Thornton, Mike Welker and research workshop participants at Queen's, KAIST, and 2012 AAA Annual Meeting in Washington D.C. for comments on previous drafts of this paper.

Do Analysts Strategically Employ Cash Flow Forecasts Revisions to Offset Negative Earnings Forecasts Revisions?

Abstract:

We investigate whether analysts use cash flow forecasts as a means of reducing the impact of earnings forecast revisions on market participants. In particular, we focus on analysts' concurrent cash flow and earnings forecast revisions that are in the opposite direction. We start by carrying out an interview-based field study with analysts and then carry out a large scale archival investigation. We find that analysts are more likely to issue concurrent positive cash flow forecast revisions when earnings forecast revisions are negative (than the opposite), particularity when following the larger complex firms that make up Fortune 500. Furthermore, while some analysts optimistically bias their cash flow forecasts, the market (i.e., investors) does not appear to penalize the bias or to account for the magnitude of cash flow forecast revisions. Finally, we examine the rationales provided in the analyst full-text reports and find that analysts attribute their opposite direction cash flow forecast revisions to changes in their forecasting model's assumption that would be difficult for an analyst to make without having access to management. Overall, the pattern of evidence suggests that analysts may strategically use cash flow forecasts in conjunction with earnings forecasts to maintain good management relationships.

Keywords: analyst, cash flow forecast; earnings forecast revision, market response

Do Analysts Strategically Employ Cash Flow Forecasts Revisions to Offset Negative Earnings Forecasts Revisions?

1. Introduction

Sell-side analysts publish equity research reports about publicly-traded companies to communicate their private information and analyses to investors.[1] These reports are claimed to be provided from an independent and impartial perspective based on careful study and modeling by expert analysts (see Berenson and Sorkin 2002; Craig 2001; Sidel 2002 for discussions of analysts' research integrity). These analyst forecasts and recommendations form the basis of the analyst's claims to be an expert informational intermediary in the capital markets (see *Thomson Reuters* 2011).

To date, researchers have identified both firm specific (e.g., earnings quality; bankruptcy risk) and analyst specific (e.g., expertise; resources available) factors affecting analysts' decisions to issue cash flow forecasts (DeFond and Hung 2003; Ertimur and Stubben 2005). We examine the incentives in the environment that provides analysts with conflicting motivations in carrying out their informational roles. On the one hand, there are the regulatory and market forces that motivate the analyst to have a reputation for accuracy and timeliness of earnings forecasts. The reputation motivation has been strengthened by regulators' monitoring and court cases over the last decade. On the other hand, the management of the firms that analysts follow puts pressure on analysts to see the company's future prospects in the same inherently optimistic fashion that

[1] The U.S. SEC defines sell-side analysts as follows: "Sell-side analysts typically work for full-service broker-dealers and make recommendations on the securities they cover. Many of the more popular sell-side analysts work for prominent brokerage firms that also provide investment banking services for corporate clients—including companies whose securities the analysts cover" (U.S. SEC *Analyzing Analyst Recommendations* 2010).

management does and tends to put limits on the analysts' access to company information for those analysts whose forecasts do not agree with management's optimism (e.g., Clement and Westphal 2008). We posit that cash flow forecasts (CFF) that receive little or no regulatory scrutiny (see U.S. Securities and Exchange Commission 2010), yet have a similarly high profile for investors, are a potential means for analysts to manage their diverse incentives strategically.

To focus our examination, we investigate a particularly unique combination of forecast circumstances, opposite direction cash flow forecasts revisions and earnings forecast revisions. We start by interviewing sell-side analysts to understand their conflicting incentives when they deliver negative earnings forecast revisions. We then adapt Hughes and Pae's (2004) signalling model to develop testable hypotheses about this setting. We test our predictions on a sample of 11,778 analyst forecasts on *I/B/E/S US Detail History* database from 1994 to 2010 contrasting Fortune 500 firms forecast behaviors (where the analyst does not have the luxury to consider dropping coverage) with other relatively smaller firms where in the presence of negative earnings news the analyst can drop coverage. We find analysts are more likely to issue CFF revisions in the opposite direction to their EFR when they issue negative EFR than when they issue positive EFR. This asymmetry between negative and positive EFRs is more pronounced for Fortune 500 companies where the analyst cannot readily drop coverage and needs to maintain management access to understand the more complex operations of such firms.

Our supplementary analyses provide evidence to support analyst strategic use of CFF in the presence of EF: 1) analysts have a tendency to issue optimistically (i.e., positively) biased CFF when they issue negative earnings forecast revisions; 2) analyst

CFF accuracy has little impact on the market; 3) the market reacts to the sign of CFF, but not to the magnitude of CFF. Overall, the results indicate that analysts are able to choose to use CFF in an effort to curry favor with management because the market does not account for their CFF accuracy.

Our study contributes to the extant literature in the following ways. First, our multi-method approach distinguishes our study from prior research, which by limiting its analysis to a large-scale database, has rarely examined analysts' direct motivations to provide additional information in a strategic fashion. Prior studies of analyst cash flow forecasts document that analysts' decisions to issue cash flow forecasts are associated with certain firm- and analyst-characteristics (e.g., DeFond and Hung 2003; Ertimur and Stubben 2005). We delve more deeply into analysts' motivations by showing that analysts may use a concurrent cash flow forecast to achieve a specific strategic result, namely an attempt to moderate the potentially negative effects to themselves from issuing a bad news earnings forecast revision.

Second, the analyst forecast bias literature (e.g., Das, Levine, and Sivaramakrishnan 1998; Lim 2001) indicates that analysts often issue optimistically biased earnings forecasts to maintain good management relationships, even if the estimates deviate from their beliefs. The empirical evidence and the theory we propose in this paper are consistent with the argument that analysts attempt to ingratiate themselves with management by using concurrent cash flow forecasts in a strategic way, so that the discordance in the two forecasts moderates the impact of the analysts' negative earnings forecast information.

Finally, our market reaction study complements prior research on the information content of analyst cash flow forecasts (e.g., Call et al. 2013). That is, while Call et al. (2013) report that analyst cash flow forecasts are informative, when we decompose the information content of CFF revision into its magnitude and relative sign (compared with concurrent earnings forecast revision), we find that the market reacts to the relative sign of CFF revision, but not to the magnitude of CFF revisions.

We proceed as follows: in the next section we provide background to our study including what is currently known about CFF being concurrently released with earnings forecasts. We then introduce our interview study. We interpret our findings in light of a modified signalling model which leads to the hypotheses that we test using a large-scale analyst forecast archival database. Finally, we discuss the implications of our research and suggest direction for future research.

2. Institutional background

Academic research (e.g., O'Brien, McNichols, and Lin 2005; Fogarty and Rogers 2005) and U.S. Securities and Exchange Commission regulatory releases (e.g., U.S. SEC *Analyzing Analyst Recommendations* 2010) show that it is highly likely that sell-side analysts had strong to overwhelming incentives to please management of covered firms in the period leading up to the events early in this century (e.g., Enron; WorldCom). This desire is evidenced by the great reluctance of analysts to issue unfavorable "sell" recommendations or issue negative earnings forecasts revisions (e.g., Barber, Lehavy, McNichols, and Trueman 2006).[2] In particular, prior research has documented that

[2] See Kadan et al. (2009) and Barber et al. (2006) for evidence on the great increase in incidence of sell recommendations post Regulation FD and Global Settlement.

analysts tend to strategically issue favorable earnings forecasts and stock purchase recommendations in order to: 1) maintain access to management's private information (Das et al. 1998); 2) generate potential future investment banking business opportunities for their employer (O'Brien et al. 2005); and 3) generate added trading commissions for their brokerage house as positive investment advice tends to generate more sales volume than negative advice does (Irvine 2001).

Since the beginning of this century, regulators and lawmakers have enacted a series of reforms via regulation [e.g., Regulation FD (see U.S. SEC 2000)] and through the courts [e.g., Global Settlement (see U.S. SEC 2005)] in an effort to achieve more independent advices from analysts about the firms they cover (U.S. SEC 2000). However, we observe that regulators mainly focused on the content of analyst's earnings forecasts and stock recommendations (U.S. SEC 2010), but not on CFF.

Despite these regulatory changes, Clement and Westphal (2008) provide evidence that CEOs continue to use favor-rendering to influence analysts and their forecasts/recommendations even after these changes and that analysts seem to attempt to reciprocate.[3] Specifically, Clement and Westphal find that analysts who downgrade stocks receive fewer favors and experience less private access to the CEOs of the firms that the analysts downgraded. They further find that analysts who are aware of other analyst's loss of favor/access to executives are less likely to downgrade in fear of losing

[3] CEOs are known to have strong preferences to highlight 'good news' and to postpone the diffusion of 'bad news.' Thus, they often strategically promote favorable investor perceptions by managing earnings and voluntarily disclosing *pro forma* earnings and/or good news cash flow forecasts (Daniel et al. 2002; Hirshleifer and Teoh 2003; Hong, Lim, and Stein 2000; Schrand and Walther 2000; Wasley and Wu 2006).

favour or of even more severe management retaliation.[4] Given these management pressures on analysts continue in the period where regulatory pressure is increasing for more independent analysis (Clement and Westphal 2008), we posit that analysts might attempt to avoid regulatory scrutiny by employing similar high profile disclosures that are not the focus of regulatory attention, that is, CFF (e.g., U.S. SEC *Analyzing Analyst Recommendations* 2010 has only brief references to CFF). Employing CFF strategically would allow analysts to achieve their objective of balancing the competing incentives of being seen as a high quality information intermediary (e.g., evidenced by accuracy in earnings forecasts and stock recommendations) with the need to "curry favor" with management so as to maintain access to the information they need in order to make these forecasts and recommendations. Consistent with this conjecture, we observe that there has been a dramatic increase in the provision of CFF over the last decade and a half; most of which occurred after Regulation FD and Global Settlement were announced (Call et al., 2013: Table 1).

There are two possible cases of opposite direction cash flow and earnings forecast revisions. In the first case we consider, sell-side analysts issue a negative EFR with a concurrent positive CFF revision. Releasing a negative EFR is consistent with analysts' incentives to maintain their credibility with investors (e.g., Hong and Kubik 2003; Hong, Kubik, and Solomon 2000; Mikhail, Walther, and Willis 1997, 1999). Yet such negative forecasts are unlikely to be received well by company management who are by nature

[4] Favor-rendering by CEOs and private access to CEOs involve the following: disseminating critical information about recent development in the industry; putting an analyst in contact with key personnel; offering to meet with an analyst's clients; recommending an analyst for job positions; and helping analysts to gain prestigious club memberships (see Clement and Westphal 2008).

optimistic about their future prospects and expect that analysts who "really" understand the company would share their optimism (Clement and Westphal 2008). Therefore, given these incentives to be accurate forecasters yet maintain good management relationships, analysts are motivated to offset the bad earnings news by highlighting good news in another high profile disclosure (i.e., a positive CFF revision).[5] In particular, Hirst, Koonce, and Venkataraman (2007: 817-818) argue that the supplemental provision of constituent components information can affect investors' judgments on the credibility of earnings forecasts. Hence, we posit that consistent with Hirst et al. a positive CFF revision released at the same time as a negative EFR should reduce the impact of the negative EFR on investors.

Second, there is the case of a positive EFR with a concurrent negative CFF revision. Here the positive earnings news does not create any dissonance in the analyst's relationship with managers. For example, Hales (2007) shows that investors' predictions of future earnings are influenced by what they would like to believe. That is, investors are prone to accept analyst earnings forecast information at face value if the information suggests they will profit from their investment (i.e., good news). However, analysts may wish to signal to the market their superior skills (e.g., Clement and Tse 2003) via releasing cash flow forecasts that suggest that accounting accruals are the main reason for the earnings forecast increase (e.g., McInnis and Collins 2008).

[5] We do not suggest that a positive CFF revision can be made whenever it suits the interests of analysts. However to the extent that analysts can time their disclosures and given the vast diversity of practice that features inconsistency in releasing CFF across time, analysts, and firms followed, there is a possibility that analysts might use this discretion to their advantage. This is the phenomena we seek to investigate in this paper, whether they do exercise this discretion in their best interests.

Concurrent cash flow and earnings forecasts

Analyst reports about equity research normally focus on, in addition to the "buy/sell" recommendations, earnings per share forecast revisions (i.e., EFR) and other summary measures of performance, most notably cash flow forecasts (e.g., Hutton, Miller, and Skinner 2003; Hirst et al. 2007). There exist at least two reasons that a CFF revision (CFFR) may be a salient information cue used by investors to contextualize EFR. First, analyst CFFR is verifiable quantitative supplemental information. Research suggests that qualitative soft-talk supplemental disclosures (i.e., "*cheap talk*" signals) do not affect market reactions to the same extent as the *ex post* verifiable EFR do (Hutton et al. 2003; Hirst et al. 2007). Indeed, Hutton et al. (2003) suggest CFFR as an example of verifiable forward-looking supplemental disclosures that condition market reactions to EFR.

Second, concurrent CFFR are likely to arrive to market participants along with the analyst buy/sell recommendations and EFR. We note that investors can monitor EFR and CFFR (i.e., changes in analysts' estimates) real-time via information intermediary services and can easily recognize whether an analyst provides both an EFR and CFFR.

3. Field Study: Interviews with analysts

In this section, we discuss our field study to understand if analysts have conflicting incentives when they deliver negative EFR. In the field study, we interviewed 12 sell-side analysts: 11 men and 1 woman in a total of fifteen interviews over 10 months (from January to November 2008) in North America.[6] We terminated our interviews when three

---

[6] Analyst interview studies tend to be of relatively small numbers given the challenges involved in obtaining access to analysts and most extant published studies were done in an era before the financial crisis of 2008. For example, Roberts et al. (2006) studied in mainly a group setting analysts following

interviewees in a row did not reveal any new information about the OPDFR phenomenon. To recruit analysts, we approached potential interviewees in Toronto and New York through three different channels: the alumni pool of a major Canadian business school; the Dean's Advisory Board of the same school; and one of the author's personal contacts from previous work experience at *Dow Jones Newswires*. Given the analysts' very intense work schedules and time pressures it sometimes took weeks or months to schedule (or reschedule, due to sudden cancellations) interviews. The interviewed analysts are affiliated with four different full service investment banks that provided such services as retail brokerage, institutional sales and trading, equity research, and investment banking.

Interview process

To gain first-hand knowledge of the interviewees' working environment and to facilitate interactions all interviews were held in person on site except for one phone interview. The average interview lasted 55 minutes with a range 40 to 75 minutes. The format of the interviews was semi-structured (Bernard 2002; see Imam, Barker, and Clubb 2008 for research on analysts) that followed a general script. The interviewer began the meeting by briefly introducing the study, himself, and describing its importance (cf. Huber and Power 1985; Spradley 1979), building an initial rapport with the interviewees (cf. Weiss 1994; Patton 2002) and reminding the interviewee both orally and in writing that we promised anonymity and confidentiality of their responses (cf. Huber and Power 1985;

thirteen UK listed companies in the aftermath of 2002 accounting scandals. Other studies are even more dated (e.g., Barker 1998, 2000 from the mid-1990s with a common set of 32 analysts focusing on analysts beliefs about EMH and understanding of accounting information more generally) albeit with a bit better access to analysts.

Young 1999; Weiss 1994). Eight of the eleven in-person interviews (including repeats) were tape-recorded with consent of the interviewee. Three other in-person interviews as well as the phone interview were not taped at the request of the interviewees. In all interviews the interviewer made notes during the interview and created a summary of the interview as soon as possible after the interview. We provided either the interview transcripts or the summary notes to all interviewees and no substantive changes occurred as a result of this feedback process.

Analysis of field interviews

Most (75%, 9 out of 12) of the interviewees suggested that they felt pressured when they decide to disseminate a negative EFR (see Table 1). However, the remaining three analysts stated that they knew that *other* analysts were influenced by interested parties' preferences or management resistance against negative EFR. Hence, given the sensitivity of the question, we conclude that all interviewed analysts have faced such pressure, either directly or indirectly.

[Insert Table 2 About Here]

Interviewees indicated that corporate managers can take analysts' downgrades highly personally, as if the analysts do not appreciate the managers' management skills. Joe (a pseudonym), who we interviewed in February 2008, stated that "managers of the issuing company are the biggest forms of resistance we get when we change our earnings estimates downwards."[7] All of the 12 interviewees indicated that they experienced management "retaliation" after they issued negative EFR similar to that reported in

[7] To protect the anonymity of the interviewees, all names used in the paper are pseudonyms and are not associated with the real names of the interviewees.

Clement and Westphal 2008. Among the forms of "retaliation" our interviewees experienced after issuing a negative EFR were senior corporate managers who would not answer the analyst's questions even when it was the corporation's own investor relations staff who had invited the analyst to visit the company. It could be construed that the invite combined with the refusal to answer questions was set up so as to make it clear to the analyst the displeasure of management with the analyst's negative EFR.

Our field study also suggests that that analysts feel strong motivations to be accurate, independent experts yet they personally need to maintain good relationships with firm managers, especially for the larger, more complex firms, in order to obtain information they need to make these expert judgments. In the following sections, we develop testable hypotheses through incorporating these incentives into a signalling model (i.e., Hughes and Pae 2004) and testing the predictions on a large scale database of analysts' forecasts.

4. Theorizing about analysts strategic use of cash flow forecasts

We start our theoretical reflections by focusing on recent analytical-economics-based research on management voluntary disclosures (e.g., Hughes and Pae 2004) then adapt a signaling model to our analysts' setting. The basic signalling model used in Hughes and Pae 2004, is based on what a firm's managers (not analysts) would do with information they had available to them about two signals of future outcomes. The model would predict that in all cases where managers have relevant information they would voluntarily provide it to the market, leading to full disclosure equilibrium. However, Hughes and Pae stylize the managers' supplemental disclosures to investors as *precision* information, which can "negate" or "reinforce" primary disclosures such as EFR. Hughes and Pae assume that information asymmetry exists between managers and investors who are uncertain about whether the managers provide certain supplemental information. Thus, Hughes and Pae's model predicts that managers supplement good (i.e., positive) and bad (i.e., negative) earnings news differentially with other value-relevant disclosures leading them to predict that a full disclosure equilibrium will not be obtained as classic signalling models would predict.

We make two modifications to the Hughes and Pae model. First, we adapt it to analyst's setting (instead of a manager's insider based disclosures, we consider analysts' forecasts), and, second, we incorporate our posited conflicting incentives that analysts experience that are different from the manager's incentives.

Combining these two modifications with the insights from Hughes and Pae's model we conclude that an analyst who discloses a negative EFR (i.e., "bad primary news" in the model's terms) has an incentive to avoid negative consequences to themselves by negating or downplaying the bad news. Analysts achieve this negation of bad news by reducing forecast users' confidence in that negative news by providing a positive CFFR (i.e., "supplemental disclosure" of precision information) that casts doubt on the interpretation of the primary bad news disclosed in the negative EFR. Thus, if the analyst is privately informed (through either additional extensive research and/or access to management's interpretation of events) of a positive CFFR (which signals the *low persistence* of the negative EFR in model terms), the analyst will voluntarily supplement the bad earnings news with the positive CFFR.

Further, in such a world, the analyst will have much less incentives to provide such negative precision information when a positive primary disclosure of EFR is made.

This analysis does not imply that analysts will never provide negative CFFR with positive EFR given that the basic signalling model results that find many states of nature of full disclosure. Rather the model combined with our two modifications suggests a relative incentive for more disclosures in the negative EFR condition.

Hence, based on both our qualitative findings and our modified signalling model we make the following prediction:

> H1. *Analysts are more likely to issue cash flow forecast revisions in the opposite direction to their earnings forecast revisions (OPDFR) when they issue "bad news" earnings forecast revisions (negative EFR) than when they issue "good news" earnings forecast revisions (positive EFR).*

Next, we consider the strength of the analyst's motivation to maintain access to managers (i.e., "curry favour") as a means of refining our prediction. Research suggests that analysts have strong incentives to follow large firms (Bhushan 1989; Marston 1997) hence they cannot drop such firms that have disappointing news the way they can for smaller firms (Rana 2008).[8] Further, our interviewed analysts stated that they have discretion when following smaller firm, the discretion that they do not have in following industry leaders. Also, the need for information from management to make accurate forecasts and recommendations is likely to be higher for analysts covering larger, more complex firms than those covering smaller less complex firms. Hence, based on analysts' ability to drop coverage of smaller firms with negative EFR combined with the analysts' need for management access to make accurate predictions about larger more complex firms, we posit that analysts will be more strategic in their use of the supplemental

[8] According to Mr. Giampaolo Trasi, vice chairman of the European Federation of Financial Analysts' Societies, analysts are very much likely to drop their coverage after three consecutive quarters of disappointing earnings all other things being equal (Rana 2008).

precision information in the case of large firms relative to smaller firms. Employing Fortune 500/others as a convenient partitioning of larger complex firms from others[9], we predict:

> H2. *Relative to analysts covering non-Fortune 500 firms, analysts covering Fortune 500 firms are more likely to issue cash flow forecast revisions in the opposite direction to their earnings forecast revisions (OPDFR) when they issue "bad news" earnings forecast revisions (negative EFR) than when they issue "good news" earnings forecast revisions (positive EFR).*

5. Analysis of large-scale database of analyst forecasts

To determine if the evidence in the large-scale archival database supports our hypotheses based on the modified signalling model, our second investigation uses the *I/B/E/S Detail History US Edition* database. We collect 'one-year ahead' annual earnings and cash flow forecasts from 1993 to 2010 in the database. We exclude forecasts issued by analysts who have not issued CFF at least once in the present year or the preceding year because the analysts may not have the discretion to publicize CFF. The sample is restricted to forecasts issued during the first 11 months of the fiscal year, (1) to be consistent with the design choices of prior studies (Clement 1999; Clement and Tse 2003, 2005) and (2) to focus on a setting where strategic concerns can dominate. Analysts who seldom update their revisions are less likely to engage in strategic uses of their forecasts.[10] We then retain only the last earnings forecast an analyst issues in a particular year (Clement 1999;

[9] Cai (2007) provides evidence that the inclusion in such indexes as S&P500 and Fortune500 means that the firm is large and hence less likely to be dropped by an analysts facing negative news.
[10] To make sure that the exclusion of stale forecasts does not drive our results, we used the "actual" last forecast revision of the fiscal year, which immediately precedes the fiscal year-end date. All results for these tests (untabulated) are qualitatively the same as those reported in the paper.

Clement and Tse 2003, 2005; O'Brien 1990; Sinha, Brown, and Das 1997).[11] After eliminating potential outliers by omitting observations with the top or bottom one percent of EFR, the full *I/B/E/S* sample consists of 11,778 firm-year-analyst observations (4,004 firm-year pairs) over the sample period (1994-2010).[12]

Descriptive statistics

Table 2 partitions the *I/B/E/S* sample into four subgroups, based on the sign (positive or negative) of EFR and CFFR. In Panel A, we report the distribution of each subgroup for the full sample. Analysts in subgroups S1 and S2 issue positive EFR, while analysts in subgroups S3 and S4 issue negative EFR. The analysts in subgroups S2 and S4 have analysts' CFFR and EFR in the same direction (i.e., SAMDFR), while analysts in S1 and S3 feature OPDFR. When issuing a positive EFR, the odds of issuing OPDFR are 0.217 (=1,129/5,191).[13] But, when issuing a negative EFR, the odds of issuing OPDFR are 0.252 (=1,100/4,358). The ratio of the odds of OPDFR for negative EFR to those for positive EFR is 1.161, suggesting that the odds of OPDFR for negative EFR are 16.1 % greater than those for positive EFR (significant at a $p<0.001$).

[Insert Table 2, About Here]

Next, in Panels B and C, we compare the incidence of analysts' issuing OPDFR when they are covering Fortune 500 companies and when they are covering non-Fortune

[11] To make sure that our choice of the last earnings forecast does not drive our results, we re-ran all tests with all forecasts by the analyst in a given year. This increases our sample size from 11,778 to 64,604. No differences in reported results were found.
[12] We also ran tests using the full *I/B/E/S* sample without eliminating potential outliers. The results were qualitatively the same whether we included or excluded potential outliers.
[13] 'Odds' are an expression of the relative likelihood that an event of interest will happen. For instance, when the probability of an event is p (therefore, the probability of no event is $1-p$), "the odds" of the event are the quotient of the two, or $\frac{p}{1-p}$.

500 companies. In Panel B, the odds of issuing OPDFR when issuing positive EFR for Fortune 500 companies are 0.197, but when issuing a negative EFR for Fortune 500 companies, the odds of issuing OPDFR are 0.274. The odds of OPDFR for negative EFR are 39.5% higher than those for positive EFR (significant at a $p<0.0001$). The results suggest that the asymmetry in issuing OPDFR between negative and positive EFR documented in Panel A becomes even more pronounced for Fortune 500 companies.

In Panel C, we show the incidence of issuing OPDFR when analysts are covering non-Fortune 500 companies. When issuing positive EFR, the odds are 0.233, and when issuing a negative EFR, the odds are 0.242. The odds of OPDFR for negative EFR are only 4% higher than those for positive EFR, and the difference is insignificant (with $p>0.50$), suggesting that the asymmetry in issuing OPDFR between negative and positive EFR documented in Panel A does not exist when analysts are covering non-Fortune 500 companies.

Tests of hypotheses

To formally test the hypotheses that the incidence of analysts' issuing OPDFR is significantly higher when analysts release negative EFR than when they release positive EFR, we estimate the following logistic regression:

$$Pr[OPDFR_{ijt}] = logit\ [\alpha_0 + \alpha_1 \times NEG\_EFR_{ijt} + \Sigma\ \alpha\ Control\ Variables + \varepsilon], \quad (1)$$

where *OPDFR* equals 1 if the analyst *i* issues a positive (negative) CFFR when the analyst issues a negative (positive) EFR on the same day for firm *j* in year *t*. The main variable of interest is *NEG_EFR* which equals 1 if the analyst *i* issues a *negative* EFR. We expect a positive coefficient on *NEG_EFR* [Hypothesis: $\alpha_1 > 0$], given we posit that it is more likely that analysts have incentives to release CFFR in the opposite direction to EFR when they provide a negative EFR than when they provide a positive EFR.

To determine the control variables required in our multivariate tests, we draw on research on analyst specific characteristics (e.g., expertise and resources available) that affects CFF availability (e.g., Clement 1999; Brown 2001, Ertimur and Stubben 2005).8 Specifically, we include the following control variables: (i) the preceding year's earnings forecast accuracy (*LAG_ACC*), which proxies for an analyst's forecasting expertise; (ii) the size of a brokerage house (*BSIZE*), which proxies for an analyst's forecasting resource; (iii) the frequency of forecasts by an analyst (*FREQ*), which indicates whether the analyst is attentive to the firm; (iv) an analyst's length of experience (*EXPF* and *EXPG*), which proxies for forecasting expertise; (v) the number of firms that an analyst follows (*NFIRM*) because the larger number of firms that an analyst covers indicates that the analyst has more expertise in forecasting; and (vi) the number of industries that an analyst follows (*NIND*) because the small number of industries that an analyst covers indicates the analyst's level of industry specialization. We also control for the timing of an analyst's forecast, relative to a preceding forecast by any analyst and relative to the end of fiscal year (*DAYS* and *FHOR*, respectively). Consistent with Clement and Tse 2005 (313), we expect the coefficients on analyst characteristics (e.g., *LAG_ACC, BSIZE*, *FREQ*, *EXPF*, and *EXPG*) to be negative; we expect the coefficients on analyst characteristics (e.g., *NFIRM* and *NIND*) to be positive; and, finally, we expect the coefficients on forecast timing (e.g., *DAYS* and *FHOR*) to be negative.

Results of hypotheses tests

In Panel A of Table 3, we provide the logit regression results of analysts' propensity to issue OPDFR for the full sample. The first two columns are the results of univariate tests (Model 1 without control variables and Model 2 with only controls for firm and year effects of forecasts). Models 3 and 4 that include control variables are the focus of our tests with the only difference between the two models being the inclusion of firm and year effect of forecast.[14] Overall, as predicted in H1 and consistent with the univariate analysis in Panel A of Table 2, the coefficient on *NEG_EFR* is significantly positive at a $p< 0.01$ level [H1: $\alpha_1 > 0$] for all four models in the full sample.[15] For example, in Models 1 and 3, the adjusted odds of issuing OPDFR when issuing negative EFR are 16.1 percent [=100 x ($e^{0.15}$-1)] greater than when issuing positive EFR.[16] Note that the adjusted odds of Models 1 and 3 are similar with the odds results in Panel A of Table 2. Further, the odds of Models 2 and 4 (27.1 %) are even greater than those in the univariate comparison in Table 2.

[Insert Table 4 About Here]

---

[14] In the *I/B/E/S* sample, we have multiple observations (analyst forecasts) per firm-year. The likelihood of OPDFR by analyst *i* for firm *j* may be associated with firm *j*'s firm-specific characteristics. Also, researchers argue that critical events in the early 2000s (the crash of the Internet bubble, the decimalization of the US stock exchanges, the demise of Enron, WorldCom's acknowledgement of accounting errors and bankruptcy filing, and the US economic recession are a few examples) have changed the information playing field for analysts and managers (e.g., Bailey et al. 2003; Heflin et al. 2003; Mohanram and Sunder 2006; Agrawal et al. 2006; Ahmed and Schneible 2007). Thus, it is possible that the above pooled logit regression results are affected by omitted explanatory variables at the cluster level of firm-year pair. To control for the firm and year fixed effects, we use the conditional maximum likelihood estimation for Models 2 and 4 (Allison 1999; Chamberlain 1980) that include year and firm effects.

[15] Unlike Models 1 and 3, Models 2 and 4 do not have intercepts because α_k parameters that represent each firm-year k (i.e., α_0 of Equation 1) are canceled out in the conditional maximum likelihood estimation (Allison 1999, 188-192).

[16] To interpret the logit regression results in terms of adjusted odds rather than the coefficient estimate *per se*, we compute the adjusted odds ratio by 100 x (e^{β}-1) where β is a coefficient estimate (see DeFond and Hung 2003).

As predicted in H2 and consistent with the univariate analysis results in Panels B and C of Table 2 for the distinction between Fortune 500 firms and others, we find that our results in Panel B for Fortune 500 companies feature larger coefficient sizes and are statistically significant. Further, the coefficients are smaller and at best marginally significant in Panel C for non-Fortune 500 (small and relatively less visible) companies.

As all firms in our sample have analysts who provide *CFF* and we control for firm fixed effect, we believe that there is no need to include firm-level control variables that predict whether at least one of analysts will issue *CFF* (e.g., DeFond and Hung, 2003). However, to make sure that our results are not affected by the firm-year effect and the omission of firm-specific factors does not drive our results, we repeated our tests including DeFond and Hung's factors and year dummy variables. Table 5 shows that our main variable of interest, *NEG_EFR*, remains significant regardless of the inclusion of the firm characteristic variables.

[Insert Table 4 About Here]

So far, we have documented that analysts' CFFR are more likely to be in the opposite direction from a negative EFR even in this broader and more representative *I/B/E/S* sample and the archival evidence is consistent with our theory of analyst strategic use of cash flow forecasts. In the following supplementary analyses, we further investigate analyst cash flow forecast accuracy and market responses.

Analyst strategic use of optimistically biased cash flow forecasts

In this subsection, we investigate whether strategic analysts "trade off" cash flow forecast accuracy for earnings forecast accuracy. In particular, we estimate the following regression:

$$\textit{CF Forecast Bias} = S1 + S2 + S3 + S4 + \textit{Lag of CF Forecast Bias}$$
$$+ \Sigma\, \alpha\, \textit{Control Variables} + \varepsilon, \qquad (2)$$

where *CF Forecast Bias* is actual cash flow forecast less forecasted cash flows and S# is an indicator variable for each of the corresponding four subgroups in Panel A, Table 2.

In Table 5, we find that the coefficient on S3 is significantly negative at a $p<0.05$ level, but the coefficients on other subgroups' indicators (S1, S2, and S4) are not statistically different from zero. We interpret this result such that analysts in subgroup S3 (who issue negative EFR and positive CFFR) have strong incentives to optimistically bias their cash flow forecasts. That is, S3 analysts are likely to sacrifice their cash flow forecast accuracy in order to issue a positive CFFR in the presence of negative EFR (bad earnings news). The positive forecast bias result is consistent with our analyst strategic use of cash flow forecasts when they issue bad earnings news (i.e., negative EFR).

[Insert Table 5 About Here]

Literature on analyst earnings forecast accuracy suggests that an analyst has a strong incentive to issue an accurate earnings forecast because investors' response to his or her earnings forecast revisions increases with the historical accuracy of the earnings forecast (e.g., Stickel 1992; Abarbanell et al. 1995; Park and Stice 2000; Chen, Francis and Jiang, 2005). If the market also cares for the historical accuracy of analyst cash flow forecast, it would be very costly for S3 analysts to "trade off" their cash flow forecast accuracy to issue optimistically biased cash flow forecasts. Thus, we estimate the following OLS regression to examine whether investors respond less strongly to cash flow forecasts by analysts whose prior cash flow forecasts were less accurate:

$$\textit{CAR}\,(-1, +1) = \textit{CFREV} + \textit{LagCF Accuracy} + \textit{CFREV*LagCF Accuracy}$$

$$+ \ EREV + LagEF\ Accuracy + CFREV{*}LagEF\ Accuracy + \ \varepsilon, \ (3)$$

where our main variable of interest is the interaction between *CFREV* and lagged cash flow forecast accuracy. The positive coefficient on the interaction would suggest that the market accounts for analyst forecast accuracy.

Model (1) in Table 6 shows that the coefficient on *CFREV*LagCF Accuracy* is insignificant, suggesting that analysts' lagged cash flow forecast accuracy does not affect the market reaction to CFFR. The cash flow forecast result is in contrast with the earnings forecast accuracy literature and our result in Model (2) where we find that the coefficient estimate on *EFREV*LagEF Accuracy* is significantly positive at the 0.10 level. We also combine earnings and cash flow forecast accuracy information together in Model (3) and find that while the market react to analysts' lagged earnings forecast accuracy, it does not react to analysts' lagged cash flow forecast accuracy. In sum, we find that the market overlooks which analysts are more accurate in their cash flow forecasts, supporting our argument that some analysts may choose to "trade off" cash flow accuracy for earnings forecast accuracy.

[Insert Table 6 About Here]

The informativeness of analyst cash flow forecasts

In this subsection, we investigate whether the informativeness of cash flow forecasts varies conditioning on analysts' strategic use of the cash flow forecasts. We first examine the information content of cash flow forecasts by estimating the following OLS regression:

$$Market\ responses \ = EFR \ + \ CFFR \ + \ \varepsilon, \qquad (4)$$

where *Market responses* are the market-adjusted, cumulative abnormal returns over the various time windows. Table 7 provides the regression results of Equation (4). First, Model (1) shows that the coefficient on *CFFR* is significantly positive at a $p<0.05$ level, and the result of Model (1) is consistent with Call, Chen, and Tong (2013) who argue that "investors behave as if analysts' cash flow forecasts are meaningful and informative predictions of future cash flows". We will re-address the result and the interpretation of Model (1) later when we discuss our findings in Table 8.

[Insert Table 7 About Here]

In Models (2)~(6), we further examine whether there exists any prolonged market reaction, price drifts or even price reversals in three months to one year post analyst forecast revision. We find that while the coefficient on *CFFR* is significantly positive for the short term window [i.e., cash flow forecast appears to be informative in Model (1)], the coefficients on *CFFR* are not statistically significant for 3-month *CAR* or longer term window regressions [Models (2)-(6)].

Based on the results in Table 7, one may conclude that the market responds to analyst cash flow forecasts in the short run, and more importantly, as there exists no prolonged market reaction or post revision price reversal, the market's short-term reaction is not evidence for the market "getting fooled" by analysts' strategic cash flow forecasts. However, we argue that such a conclusion is premature as our analysis in Table 7 ignored analysts' strategic motivation by indiscriminating the relative sign of *EFR* and *CFFR*. To address analyst strategic use of CFF, we separately examine the informativeness of CFF across the four subgroups suggested in Table 2. In particular, we estimate the following regression:

$$
\begin{aligned}
\textit{Market responses} = {} & S1 + S2 + S3 + S4 \\
& + EFR*S1 + CFFR*S1 \\
& + EFR*S2 + CFFR*S2 \\
& + EFR*S3 + CFFR*S3 \\
& + EFR*S4 + CFFR*S4 + \varepsilon. \qquad (5)
\end{aligned}
$$

Note that estimating Equation (5) is equivalent to estimating Equation (4) separately for each subgroup. In separately regressing the model for each subgroup, we attempt to decompose CFFR information into two: the information reflected in the relative sign of the revision and the information reflected in the magnitude of the revision

Table 8 reports the regression results of Equation (5). First, regarding the information content of the magnitude of CFFR, we find that coefficients on *CFFR*S#* are statistically insignificant except the coefficient on *CFFR*S2*. It is interesting that *CFFR* for S2 is informative (i.e., its coefficient estimate is marginally significant). It may be interpreted such that the market reacts only to a positive *CFFR* (i.e., as a positive reinforcer) in the presence of a positive EFR, but not in the presence of a negative EFR. Overall, unlike the results in Table 7, the results in Table 9 suggest that analyst cash flow forecast revisions (*CFFR*) may not be informative once we control for the relative sign of CFFR. This supports the importance of considering the relative sign of earnings and cash flow forecast revisions.

[Insert Table 8 About Here]

Second, regarding the information content of the magnitude of earnings forecast revision (EFR), we find that all four coefficients on the interaction between *EFR*S#* are statistically significant, suggesting that the market finds the magnitude of EFR informative even when we control for the relative sign of CFFR. More interestingly, we find that, in the 3-day CAR regression of Model (1), the coefficient on *EFR*S3* is noticeably larger than that on *EFR*S4* (0.719 versus 0.463). Given that both S3 and S4 subgroup analysts issue negative EFR, the 3-day CAR result suggests that the market's unfavorable short-term price reaction to negative earnings forecast revisions is more pronounced when analysts issue *OPDFR* than *SAMEFR*. This is interesting in that the market responds more strongly to the bad earnings news accompanied by positive CFFR (i.e., OPDFR) than to the bad earnings news accompanied by negative CFFR (i.e., with a negative reinforcer). This suggests that the market does not get "fooled" by the optimistic cash flow forecast. In other words, if analysts attempt to mitigate the negative impact of the bad earning news by issuing *OPDFR*, the strategy does not work at least in terms of the market reaction to the magnitude of the negative earnings forecast revisions. Note that the result is consistent with our field study indicating that managers of the issuing companies, not investors, are the biggest form of resistance toward negative EFR.

6. Analysis of full-text analyst reports

As our field study suggests that that analysts are under more pressure to issue OPDFR when they cover Fortune 500 firms, we lastly investigate analyst research reports from *Thomson Research* database with a goal to document analysts' justifications in releasing OPDFR. We first identify 272 reports that contain a CFFR and find that among the 272 analyst research reports, 73 (26.8%) contain OPDFR (28 positive EFR and 45 negative EFR reports).[17] We limited this analysis to the period covering 1999 to 2005 that

[17] Consistent with Panel B of Table 2, the odds of issuing OPDFR are much greater when issuing a negative EFR than when issuing positive EFR [0.80 versus 0.20, a significant difference at $p<0.05$].

had at least one analyst who issued OPDFR when delivering positive EFR and at least one analyst who issues OPDFR when delivering negative EFR over the sample period because this period was congruent with our initial I/B/E/S sample that we subsequently expanded to provide greater generalizability.[18]

We then analyze each of the 73 analysts' reports searching for justifications for provision of OPDFR using keyword searches. Table 9 documents the set of reasons (or explanations) analysts provided for issuing OPDFR in their full-text reports. The most common reason for issuing OPDFR is that analysts expect a change related to taxes, especially deferred taxes with 10 of 26 negative EFR reports (38%) and 5 of 11 positive EFR reports (45%). The second most common reason for OPDFR was different between negative and positive EFR. Negative EFR reports highlight changes in assumptions about inventories and other current assets whereas changes in overall cost structures is the second most common reason for OPDFR when analysts issue positive EFR.

[Insert Table 9 About Here]

We divide the rationales in Table 9 into those that would require or at least greatly benefit from having access to management versus those that could be inferred with publicly available (i.e., changes in input prices on the market) information. We see from Table 9 that reasons for positive and negative EFR are somewhat different. In particular, negative EFR reports justify positive CFFR by referring to increases in operating cash

[18] The *Thomson Research* database features extensive analyst equity reports from over 980 investment banks, brokerage houses, and research firms, covering 30,000 companies worldwide. However, its coverage is still narrower than that of I/B/E/S, especially during 1990s as it has a relatively short history. To minimize the mismatch between the two databases, we narrow down our hand collection of analyst reports to *Fortune 500* firms (i.e., large firms) for the sample period after 1999. Still, we had to exclude two of the 31 pairs from I/B/E/S for which the *Thomson Research* database does not have any analyst report available or does not have an opposite direction CFF report with a positive EFR.

inflows (e.g., “a favorable shift in the mix of self-pay receivables” or “upfront cash collections”) or to a revaluation of fixed assets (e.g., “an increase to the DD&A rate” or “a non-cash impairment charge”) in analysts’ forecasting models.

Our analysis of the full-text analysts’ reports of Fortune 500 firms corroborates our finding that analysts have both set of incentives (accuracy as an independent information intermediary and needs for access to management), which motivate analysts’ strategic use of CFFR when they deliver bad news in earnings.

7. Discussion and Conclusion

We provide a multi-method perspective on the underlying causes of analysts’ issuing cash flow forecasts in addition to earnings forecasts when cash flow forecast revisions are in the opposite direction to earnings forecast revisions. First, our interview study showed that the need to maintain access to management is an important constraint when analysts deliver a negative EFR. Second, the large scale database study shows that the prevalence of such opposite direction positive CFFR with negative EFR occurs to the greatest extent among the set of firms, the Fortune 500, where analysts need to continue coverage but also have to have access to management to understand the more complex environment as compared to the smaller firms where ongoing negative EFR can be dealt with by dropping coverage. Third, our market analysis indicates the importance of considering the relative sign of CFFR and EFR. Finally, the full-text analysis suggests that analysts’ rationales in releasing OPDFR are more dependent on access to management when there is a negative EFR than a positive EFR. Overall, our additional analyses corroborate our story about strategic use of OPDFR.

The complementary and corroborating nature of this research should reinforce the conclusions that we have made whilst motivating future research in this area. Such research could include examining the relative size of forecast revisions (i.e., CFFR versus EFR) being used to moderate or to reinforce the direction of the news in the EFR. Given that we have documented that analysts strategically employ opposite direction CFFR to EFR, this would seem to be one logical extension of our research. Further, our field research on analysts' forecasting activities does not directly address the political and social aspects of analysts in capital markets (e.g., Roberts et al. 2006). Future research may expand the paper into two directions: 1. Expanding the field study, for example interviewing corporate managers of firms analysts cover, sales persons of brokerages, investors, and analysts for the same firm to provide more insights into this issue; 2. Extending the archival study by examining other possible ways for strategic analysts to keep managers happy when issuing negative earnings forecasts, for examples favorable long-term earnings forecasts or stock recommendation (e.g., Lin and McNichols, 1998; Dechow et al., 2000).

References

Abarbanell, J., W. Lanen, and R. Verrecchia. 1995. Analysts' forecasts as proxies for investor beliefs in empirical research. Journal of Accounting and Economics 20 (1): 31–60.

Agrawal, A., Chadha, S. and Chen M. A. (2006) Who is afraid of Reg FD? The behavior and performance of sell-side analysts following the SECs Fair Disclosure Rules, *Journal of Business*, 79(6), pp. 2811–2834.

Ahmed, A. S. and Schneible A. S. Jr. (2007) The impact of Regulation fair disclosure on investors prior information quality – Evidence from an analysis of changes in trading volume and stock price reactions to earnings announcements, *Journal of Corporate Finance*, 13(2–3), pp. 282–299.

Allison, P. (1999) *Logistic regression using the SAS system: Theory and application*. (Cary, NC: SAS Institute Inc).

Bailey, W., Li, H., Mao, C. and Zhong, R. (2003) Regulation fair disclosure and earnings information: Market, analyst, and corporate responses, *The Journal of Finance*, 58(6), pp. 2487–2514.

Barber, B., Lehavy, R., McNichols, M. and Trueman, B. (2006) Buys, holds, and sells: The distribution of investment banks stock ratings and the implications for the profitability of analysts recommendations, *Journal of Accounting and Economics*, 41(1–2), pp. 87–117.

Barker, R. (1998) The market for information: evidence from finance directors, analysts and fund managers, *Accounting and Business Research*, 29(1), pp. 3–20.

Barker, R. (2000) FRS3 and analysts use of earnings, *Accounting and Business Research*, 30(2), pp. 95–109.

Berenson, A. and Sorkin, A. R. (2002) How Wall Street was tamed, *New York Times*, 22 (December): 1, C3.

Bernard, H. R. (2002) Interviewing: Unstructured and semistructured, in: *Research methods in anthropology – Qualitative and quantitative approaches*, Chapter 9 (Walnut Creek, CA: AltaMira Press).

Bhushan, R. (1989) Firm characteristics and analyst following, *Journal of Accounting and Economics*, 11(2), pp. 255–274.

Brown, L. (2001) How important is past analyst forecast accuracy?, *Financial Analysts Journal*, 576(6), pp. 44–49.

Cai, J. (2007) What's in the news? Information content of S&P 400 Additions, *Financial Management*, 36(3), pp. 113–124.

Call, A. C., Chen, S. and Tong, Y. H. (2013) Are analysts cash flow forecasts naïve extensions of their own earnings forecasts?, *Contemporary Accounting Research*, forthcoming.

Chamberlain, G. (1980) Analysis of covariance with qualitative data, *Review of Economic Studies,* 47(1), pp. 225–238.

Chen, Q., Francis, J. and Jiang, W. (2005) Investor Learning About Analyst Predictive Ability. *Journal of Accounting and Economics*, 39 (1), 3-24.

Clement, M. (1999) Analyst forecast accuracy: Do ability, resources, and portfolio complexity matter?, *Journal of Accounting and Economics*, 27(3), pp. 286–303.

Clement, M. and Tse, S. (2003) Do investors respond to analysts forecast revisions as if forecasting accuracy is all that matters?, *The Accounting Review,* 78(1), pp. 227–249.

Clement, M. and Tse, S. (2005) Financial analyst characteristics and herding behavior in forecasting, *The Journal of Finance,* 60(1), pp. 307–341.

Clement, M. and Westphal, J. D. (2008) Sociopolitical dynamics in relations between top managers and security analysts: Favor rendering, reciprocity, and analyst stock recommendations, *Academy of Management Journal* 51(5), pp. 873–897.

Craig, S. (2001) Unions put pressure on Wall Street over analysts conflicts of interest, *Wall Street Journal*, October 29, J, C15.

Daniel, K. D., Hirshleifer, D. and Teoh, S. H. (2002) Investor psychology in capital markets: Evidence and policy implications, *Journal of Monetary Economics,* 49(1), pp. 139–209.

Das, S., Levine, C. B. and Sivaramakrishnan, K. (1998) Earnings predictability and bias in analysts earnings forecasts, *The Accounting Review,* 73(2), pp. 277–294.

Dechow, P. M., Hutton, A. P. and Sloan, R. G. (2000) The Relation between Analysts' Forecasts of Long- Term Earnings Growth and Stock Price Performance Following Equity Offerings, *Contemporary Accounting Research* 17 (1), pp. 1-32.

Defond, M. and Hung, M. (2003) An empirical analysis of analysts cash flow forecasts, *Journal of Accounting and Economics,* 35(1), pp. 73–100.

Ertimur, Y. and Stubben, S. (2005) Analysts incentives to issue revenue and cash flow forecasts, Working Paper, Stanford University.

Fogarty, T. J. and Rogers, R. K. (2005) Financial analysts reports: An extended institutional theory evaluation, *Accounting, Organizations and Society*, 30(4), pp. 331–356.

Givoly, D., Hayn, C. and Lehavy, R. (2009) The quality of analysts cash flow forecasts, *The Accounting Review,* 84(6), pp. 1877–1911.

Hales, J. (2007) Directional preferences, information processing, and investors forecasts of earnings, *Journal of Accounting Research,* 45(3), pp. 607–628.

Heflin, F., Subramanyam, K. R. and Zhang, Y. (2003) Regulation FD and the financial information environment: Early evidence, *The Accounting Review,* 78(1), pp. 1–37.

Hirshleifer, D. and Teoh, S. H. (2003) Limited attention, information disclosure, and financial reporting, *Journal of Accounting and Economics,* 36(1–3), pp. 337–386.

Hirst, D. E., Koonce, L. and Venkataraman, S. (2007) How disaggregation enhances the credibility of management earnings forecasts, *Journal of Accounting Research,* 45(4), pp. 811–837.

Hong, H. and Kubik, J. (2003) Analyzing the analysts: Career concerns and biased earnings forecasts, *The Journal of Finance,* 58(1), pp. 313–351.

Hong, H., Kubik, J. and Solomon, A. (2000) Security analysts career concerns and herding of earnings forecasts, *Rand Journal of Economics,* 31(1), pp. 121–144.

Hong, H., Lim, T. and Stein, J. (2000) Bad news travels slowly: Size, analyst coverage and the profitability of momentum strategies, *The Journal of Finance,* 55(1), pp. 265–295.

Huber, G. P. and Power, D. J. (1985) Respective reports of strategic-level managers: Guidelines for increasing their accuracy, *Strategic Management Journal,* 6(2), pp. 171–180.

Hughes, J. and Pae, S. (2004) Voluntary disclosure of precision information, *Journal of Accounting and Economics,* 37(2), pp. 261–289.

Hutton, A. P., Miller, G. S. and Skinner, D. J. (2003) The role of supplementary statements with management earnings forecasts, *Journal of Accounting Research,* 41(5), pp. 867–890.

Imam, S., Barker, R. and Clubb, C. (2008) The use of valuation models by UK investment analysts, *European Accounting Review*, 17 (3), pp. 503-535.

Irvine, P. (2001) Do analysts generate trade for their firms? Evidence from the Toronto Stock Exchange, *Journal of Accounting and Economics,* 30(2), pp. 209–226.

Kadan, O., Madureira, L., Wang, R. and Zach, T. (2009) Conflicts of interest and stock recommendations – the effect of the Global Settlement and related regulations, *Review of Financial Studies,* 22(10), pp. 4189–4217.

Lim, T. (2001) Rationality and analysts forecast bias, *The Journal of Finance,* 56(1), pp. 369–385.

Lin, H.-W. and McNichols, M. F. (1998) Underwriting relationships, analysts' earnings forecasts and investment recommendations, *Journal of Accounting and Economics*, 25 (1), pp. 101-127.

Marston, C. (1997) Firm characteristics and analyst following in the UK, *British Accounting Review,* 29(4), pp. 335–347.

McInnis, J. M. and Collins, D. W. (2010) The effect of cash flow forecasts on accrual quality and benchmark beating, *Journal of Accounting and Economics*, 51, pp. 219-239.

Mikhail, M., Walther, B. and Willis, R. (1997) Do security analysts improve their performance with experience?, *Journal of Accounting Research,* 35(2), pp. 131–157.

Mikhail, M., Walther, B. and Willis, R. (1999) Does forecast accuracy matter to security analysts?, *The Accounting Review,* 74(2), pp. 185–200.

Mohanram, P. S. and Sunder, S. V. (2006) How has regulation fair disclosure affected the functioning of financial analysts?, *Contemporary Accounting Research,* 23(2), pp. 491–526.

OBrien, P. (1990) Forecast accuracy of individual analysts in nine industries, *Journal of Accounting Research,* 28(2), pp. 286–304.

OBrien, P., McNichols, M. and Lin, H. W. (2005) Analyst impartiality and investment banking relationships, *Journal of Accounting Research,* 43(4), pp. 623–650.

Park, C., and E. Stice. 2000. Analyst forecasting ability and the stock price reaction to forecast revisions. Review of Accounting Studies 5 (3): 259–272.

Patton, M. Q. (2002) *Qualitative Research and Evaluation Methods*, 3rd ed. (Thousand Oaks,

Roberts, J., Sanderson, P., Barker, R. and Hendry, J. (2006) In the mirror of the market: The disciplinary effects of company/fund manager meetings, *Accounting, Organizations and Society,* 31(3), pp. 277–294.

Schrand, C. and Walther, B. (2000) Strategic benchmarks in earnings announcements: The selective disclosure of prior-period earnings components, *The Accounting Review*, 75(2), pp. 151–177.

Sidel, R. (2002) SEC plan would make analysts certify their recommendations, *Wall Street Journal*, 24(September): J, C16.

Sinha, P., Brown, L. and Das, S. (1997) A re-examination of financial analysts differential earnings forecast accuracy, *Contemporary Accounting Research,* 14(1), pp. 1–42.

Stickel, S. 1992. Reputation and performance among security analysts. Journal of Finance 47 (5): 1811–1836.

Spradley, J. P. (1979) *The ethnographic interview*. (New York, NY: Harcourt, Brace, Janovich).

Thomson Reuters (2011) StarMine analyst awards for excellence. Available at http://excellence.thomsonreuters.com/award/starmines.

U.S. Securities and Exchange Commission (2000) Selective disclosure and insider trading. Available online at http://www.sec.gov/rules/final/33-7881.htm.

U.S. Securities and Exchange Commission (2005) The global research analyst settlement. Available online at http://www.sec.gov/spotlight/globalsettlement.htm.

U.S. Securities and Exchange Commission (2010) Analyzing analyst recommendations. Available online at http://www.sec.gov/investor/pubs/analysts.htm.

Wasley, C. and Wu, J. S. (2006) Why do managers voluntarily issue cash flow forecasts?, *Journal of Accounting Research*, 44(2), pp. 389–429.

Weiss, R. S. (1994) *Learning from strangers: The art and method of qualitative interview studies*. (New York, NY: The Free Press).

Young, S. M. (1999) Field research methods in management accounting, *Accounting Horizons*, 13(1), pp. 76–84.

TABLE 1
Tabulation of key interview responses on the delivery of negative news earning forecast (NEG_EFR)

		Total	
		Count	%
(Y/N)	Pressure of issuing NEG_EFR (*Do you ever feel pressure when you revise earnings forecasts downwards, compared to when you revise forecasts upwards?*)	9	75%
(OE)	Sources of the pressure		
	Managers	7*	
	Investors	6	
	Self-pressure	4	
	Internal (investment bankers and sales forces)	3	

* Including those interviewees who talked about cases where others felt pressure but they did not.

TABLE 2
Descriptive Statistics for Opposite Direction Cash Flow Forecasts from Earnings Forecast Revisions

Panel A: Full Sample (N=11,778)

Direction of CFFR	Positive EFR			Negative EFR			Test of difference in OPDFR (p-value)[a]
	Obs.	Percent	subgroups	Obs.	Percent	subgroups	
OPDFR	1,129	17.9	**S1**	1,100	20.2	**S3**	(0.0016)
SAMDFR	5,191	82.1	**S2**	4,358	79.8	**S4**	
TOTAL	6,320	100		5,458	100		11,778

Panel B: Fortune 500 subsample (N=4,425 out of 11,778)

Direction of CFFR	Positive EFR			Negative EFR			Test of difference in OPDFR (p-value)[a]
	Obs.	Percent	subgroups	Obs.	Percent	subgroups	
OPDFR	428	16.4	**S1**	392	21.5	**S3**	(0.0001)
SAMDFR	2,176	83.6	**S2**	1,429	78.5	**S4**	
TOTAL	2,604	100		1,821	100		4,425

Panel C: Non-Fortune500 subsample (N=7,353 out of 11,778)

Direction of CFFR	Positive EFR			Negative EFR			Test of difference in OPDFR (p-value)[a]
	Obs.	Percent	subgroups	Obs.	Percent	subgroups	
OPDFR	701	18.9	S1	708	19.5	S3	(0.5118)
SAMDFR	3,015	81.1	S2	2,929	80.5	S4	
TOTAL	3,716	100		3,637	100		7,353

[a] *p*-value of a *Z*-test (one-tailed) of whether the proportion of analysts who issue a concurrent cash flow forecast revision in the opposite direction to an earnings forecast revision when issuing negative EFR is higher than when issuing positive EFR.

Abbreviations
CFFR = cash flow forecast revision
EFR = earnings forecast revision
OPDFR = cash flow forecast revision in the opposite direction to earnings forecast revision direction
SAMDFR = cash flow forecast revision in the same direction as earnings forecast revision direction

TABLE 3
Logit Analysis of Opposite Direction Cash Flow Forecasts Revisions from Earnings Forecast Revisions, N=11,778

		Panel A. Full Sample (N=11,778)				**Panel B. Fortune500 subsample (N=4,425)**		**Panel C. Non-Fortune500 subsample (N=7,353)**	
Variables	Pred. sign	Model 1	Model 2	Model 3	Model 4	Model 3	Model 4	Model 3	Model 4
Intercept	-	-1.53 (0.00)	n/a	-1.41 (0.00)	n/a	-1.61 (0.00)	n/a	-1.31 (0.00)	n/a
NEG_EFR	**+**	**0.15 (0.00)**	**0.23 (0.00)**	**0.15 (0.00)**	**0.24 (0.00)**	**0.34 (0.00)**	**0.43 (0.00)**	**0.04 (0.54)**	**0.14 (0.10)**
DAYS	-			0.01 (0.82)	-0.01 (0.90)	0.03 (0.76)	0.04 (0.78)	0.02 (0.76)	-0.02 (0.88)
FHOR	-			-0.21 (0.00)	-0.31 (0.00)	-0.06 (0.63)	0.05 (0.78)	-0.29 (0.00)	-0.47 (0.00)
LAG_ACC	-			0.07 (0.25)	0.03 (0.76)	0.27 (0.01)	0.14 (0.35)	-0.03 (0.75)	-0.03 (0.81)
BSIZE	-			-0.53 (0.00)	-0.68 (0.00)	-0.8 (0.00)	-0.91 (0.00)	-0.39 (0.00)	-0.57 (0.00)
FREQ	-			0.16 (0.03)	0.21 (0.03)	0.37 (0.00)	0.54 (0.00)	0.06 (0.51)	0.07 (0.57)
EXPF	-			-0.06 (0.38)	-0.06 (0.55)	0.03 (0.81)	0.12 (0.49)	-0.08 (0.34)	-0.1 (0.34)
EXPG	-			0.08 (0.31)	-0.03 (0.75)	-0.11 (0.43)	-0.22 (0.27)	0.17 (0.08)	0.03 (0.82)
NFIRM	+			0.04 (0.65)	0.06 (0.59)	0.11 (0.44)	0.03 (0.87)	0 (0.99)	0.06 (0.65)
NIND	+			0.04 (0.63)	0 (0.99)	-0.08 (0.54)	-0.03 (0.87)	0.09 (0.34)	0.004 (0.97)
Firm and Year Fixed Effects		*uncontrolled*	*controlled*†	*uncontrolled*	*controlled*†	*uncontrolled*	*controlled*†	*uncontrolled*	*controlled*†
Pseudo R2		0.001	0.001	0.015	0.009	0.034	0.015	0.010	0.008

† The conditional maximum likelihood estimation (controlling for the firm and year fixed effects).

Variable Definitions:

NEG_EFR_{ijt} = an indicator variable that equals 1 if analyst *i* issues a downward earnings forecast revision (i.e., bad news). It equals 0 if the analyst issues an upward earnings forecast revision (i.e., good news).

$DAYS_{dijt}$ = the number of days between analyst *i*'s earnings forecast date *d* for firm *j* in year *t* and the most recent earnings forecast for firm *j* by any analysts.

$FHOR_{ijt}$ = the number of days between analyst *i*'s earnings forecast date in year t and the end of fiscal period.

ACC_{ijt} = the earnings forecast accuracy in year *t*, calculated as the maximum absolute earnings forecast error for analysts following firm *j* in year *t* minus the absolute earnings forecast error of analyst *i* for firm *j* in year *t* divided by the range of absolute earnings forecast errors for analysts following firm *j* in year *t*:

$$ACC_{ijt} = \frac{max(AFE_{jt}) - AFE_{ijt}}{range\ (AFE_{jt})},$$

where AFE_{ijt} is the absolute value of analyst *i*'s earnings forecast error for firm *j* in year *t*.

$BSIZE_{ijt}$ = the size of brokerage houses employing analyst *i* in year *t*, measured by the number of analysts employed by the brokerage house.

$FREQ_{ijt}$ = the frequency of earnings forecasts by analyst *i* for firm *j* in year *t*.

$EXPF_{ijt}$ = the number of years that analyst *i* has issued earnings forecasts for firm *j*.

$EXPG_{ijt}$ = the number of years that analyst *i* has issued earnings forecasts for any firm.

$NFIRM_{it}$ = the number of firms that analyst *i* follows in year *t*.

$NIND_{it}$ = the number of (two-digit SICs) industries that analyst *i* follows in year *t*.

We control for the firm and year effect on analyst characteristics by scaling each characteristic to range from 0 to 1, for each firm-year as follows (Clement & Tse, 2003, 2005; Brown et al., 2006):

$$Characteristics_{ijt} = \frac{Characteristics_{ijt} - min(Characteristics_{jt})}{range\ (Characteristics_{jt})}.$$

TABLE 4

The estimation results of Equation (1) when DeFond and Hung's (2003) firm characteristics are controlled.

		Full sample (N=9,293[Ψ])		Fortune 500 subsample (N=4,081)		Non-Fortune 500 subsample (N=5,212)	
Variables	Pred. sign	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Intercept	-	-1.36 (0.00)	n/a	-1.64 (0.00)	n/a	-1.5 (0.00)	n/a
NEG_EFR	+	**0.22 (0.00)**	**0.31 (0.00)**	**0.34 (0.00)**	**0.46 (0.00)**	**0.13 (0.07)**	**0.2 (0.02)**
DAYS	-	0.005 (0.95)	0.01 (0.90)	0.01 (0.95)	0.02 (0.85)	0.03 (0.74)	0.01 (0.92)
FHOR	-	-0.23 (0.01)	-0.27 (0.00)	-0.03 (0.80)	0.03 (0.85)	-0.37 (0.00)	-0.53 (0.00)
LAG_ACC	-	0.16 (0.03)	0.13 (0.12)	0.32 (0.01)	0.34 (0.01)	0.05 (0.59)	-0.04 (0.70)
BSIZE	-	-0.57 (0.00)	-0.66 (0.00)	-0.69 (0.00)	-0.77 (0.00)	-0.48 (0.00)	-0.62 (0.00)
FREQ	-	0.29 (0.00)	0.23 (0.01)	0.44 (0.00)	0.4 (0.01)	0.19 (0.08)	0.08 (0.52)
EXPF	-	0.001 (0.99)	-0.01 (0.89)	0.08 (0.56)	0.08 (0.63)	-0.03 (0.75)	-0.07 (0.54)
EXPG	-	0.02 (0.79)	-0.02 (0.85)	-0.14 (0.36)	-0.11 (0.52)	0.13 (0.24)	0 (0.98)
NFIRM	+	0.07 (0.43)	0.09 (0.41)	0.07 (0.65)	0.07 (0.70)	0.07 (0.56)	0.14 (0.32)
NIND	+	0.01 (0.90)	0.01 (0.92)	-0.02 (0.87)	-0.01 (0.96)	0.02 (0.83)	-0.01 (0.92)
magnitude of accruals		0.7 (0.03)	0.2 (0.68)	-0.52 (0.49)	-2.82 (0.01)	1.05 (0.01)	0.88 (0.14)
accounting choice heterogeneity		-0.71 (0.00)	-0.08 (0.82)	-0.27 (0.34)	-0.38 (0.52)	-1.01 (0.00)	0.05 (0.92)
earnings volatility		-0.001 (0.77)	na[¶]	0.01 (0.18)	na[¶]	-0.01 (0.35)	na[¶]
capital intensity		-0.04 (0.02)	-0.06 (0.16)	-0.02 (0.53)	0.06 (0.49)	-0.05 (0.01)	-0.08 (0.14)
Altman Z		-0.03 (0.00)	-0.02 (0.34)	-0.04 (0.03)	0.03 (0.67)	-0.03 (0.01)	0.01 (0.76)
Log (Size)		0.01 (0.57)	0.08 (0.37)	0.01 (0.73)	0.004 (0.98)	0.06 (0.05)	0.04 (0.76)
Firm clustering effect		-	*Included*	-	*Included*	-	*Included*
Year fixed effect		-	*Controlled*	-	*Controlled*	-	*Controlled*
Pseudo R2		0.0241	0.015	0.0335	0.0268	0.0271	0.0179

Ψ the sample size is reduced from the original Table 2's N=11,778 while calculating DeFond and Hung's firm characteristics variables using *COMPUSTAT* database.

¶ Earnings volatility variable is not compatible with controlling for firm-specific clustering effect because only a single earning volatility variable is computed for a firm throughout the sample period (see DeFond and Hung, 2003).

TABLE 5
Cash flow forecast bias regression, N = 7,354

Independent variables \ Dependent variable	CF Forecast Bias	
S1 (+EFR, -CFFR) - OPDFR	-0.001	(-0.324)
S2 (+EFR, +CFFR) - SAMEFR	-0.005	(-1.452)
S3 (- EFR, +CFFR) - OPDFR	-0.009**	(-2.540)
S4 (- EFR, - CFFR) - SAMEFR	-0.005	(-1.306)
Lag of CF Forecast Bias	0.101***	(2.660)
Lag of CF Accuracy	-0.129***	(-4.272)
NFIRM_cf	-0.000	(-0.788)
NIND_cf	0.001	(1.618)
FREQ_cf	0.000	(0.377)
HORIZON_cf	-0.000	(-0.672)
DaysElpased_cf	0.000	(1.005)
FEXP_cf	-0.000	(-1.149)
GEXP_cf	0.000	(1.502)
BSIZE	0.000*	(1.762)
Adjusted R2	0.037	

Variable definitions:

CF Forecast Bias = (Actual CF - Forecasted CF)/stock price, where stock price is the stock price on the last trading day of the month in which the CF forecast is released.

"_cf" indicates that the variable is measured based on the analyst's cash flow forecast activities.

BSIZE is the number of analysts employed by the brokerage house in a year. To better capture the real size of the brokerage house, I use earnings forecast information to count the number of analysts.

Lag of CF Accuracy = -1*abs(Actual CF - Forecasted CF)/stock price, where stock price is the stock price on the last trading day of the month in which the CF forecast is released.

TABLE 6
Market reaction to analyst cash flow forecast accuracy, N=10,836

Independent Variables \ Dependent Variable	3-day CAR	3-day CAR	3-day CAR
	Model (1)	Model (2)	Model (3)
CFREV	0.423***		0.158***
	(6.950)		(2.650)
LagCFAccuracy	0.010		0.006
	(0.931)		(0.534)
CFREV_lagcfaccuracy	0.464		0.502
	(1.551)		(1.260)
EREV		0.949***	0.834***
		(9.868)	(7.982)
LagEFAccuracy		0.020	0.013
		(0.709)	(0.439)
EREV_lagefaccuracy		2.090*	1.457*
		(1.834)	(1.705)
Intercept	0.001	0.002**	0.002**
	(1.603)	(2.060)	(2.220)
Number of observations	10,836	10,836	10,836
Adjusted R2	0.016	0.033	0.034

Variable definitions:

LagEF(CF)Accuracy = Lag of an analyst's earnings (cash flow) forecast accuracy for a firm in a year. Forecast accuracy is defined as -1*abs(actual - forecast)/closing stock price of the month in which the forecast is made. Accuracy is measured based on an analyst's last forecast for a firm-year.

LagEF(CF)FE = Lag of an analyst's earnings (cash flow) forecast error for a firm in a year. Forecast error is defined as (actual - forecast)/closing stock price of the month in which the forecast is made. Forecast error is measured based on an analyst's last forecast for a firm-year.

TABLE 7
Market reaction to cash flow forecast revision tests for the full sample, N = 15,864

Dependent Variable	3-day CAR	3-month CAR	6-month CAR	9-month CAR	12-month CAR	Post-revision price drift
Independent Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
EFR	0.944***	0.821***	-0.017	-0.209	0.222	-0.701
	(10.914)	(3.106)	(-0.049)	(-0.580)	(0.469)	(-1.467)
CFFR	0.102**	0.152	-0.123	-0.095	-0.139	-0.268
	(2.178)	(1.088)	(-0.634)	(-0.423)	(-0.522)	(-1.001)
Intercept	0.003***	0.029***	0.081***	0.093***	0.106***	0.103***
	(3.594)	(10.678)	(19.286)	(17.404)	(15.135)	(15.012)
Adjusted R2	0.039	0.004	-0.000	0.000	-0.000	0.001

Variable definitions:

3-day CAR = market-adjusted, cumulative abnormal returns over the three-day window (-1,+1), where day 0 is the trading day of an earnings forecast revision.

3, 6, 9, 12-month CAR = market-adjusted, cumulative abnormal returns over the next three-, six-, nine-, twelve-month window [(-1,+64), (-1,+127), (-1,+190), (-1,+253)], where day 0 is the trading day of an earnings forecast revision.

Post-revision price drift = market-adjusted, cumulative abnormal returns over the window (+2,+253), where day 0 is the trading day of an earnings forecast revision.

EFR = earnings forecast revision, scaled by a closing stock price of the month of the prior earnings forecast.

CFFR = cash flow forecast revision, scaled by a closing stock price of the month of the prior cash flow forecast.

TABLE 8
Market reaction to cash flow forecast revision tests for each subgroups, N = 15,864

Dependent Variable	3-day CAR	3-month CAR	6-month CAR	9-month CAR	12-month CAR	Post-revision price drift
Independent Variables	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
S1 (+, -) OPDFR	0.007***	0.028***	0.063***	0.072***	0.077***	0.070***
	(2.700)	(4.252)	(6.550)	(5.822)	(5.296)	(4.800)
S2 (+, +) SAME	0.013***	0.030***	0.069***	0.086***	0.096***	0.083***
	(10.573)	(8.137)	(11.276)	(11.346)	(9.613)	(8.274)
S3 (-, +) OPDFR	-0.005*	0.017**	0.069***	0.079***	0.103***	0.109***
	(-1.911)	(2.263)	(5.736)	(5.897)	(6.027)	(6.784)
S4 (-. -) SAME	-0.011***	0.014***	0.064***	0.078***	0.084***	0.095***
	(-7.713)	(3.082)	(9.565)	(8.805)	(7.412)	(8.634)
*EFR*S1*	0.531*	1.432*	2.782**	2.057	2.917**	2.309
	(1.777)	(1.699)	(2.268)	(1.542)	(2.017)	(1.627)
*EFR*S2*	0.435***	1.442***	2.084***	2.378***	3.183***	2.711***
	(2.654)	(2.812)	(2.924)	(3.072)	(3.204)	(2.769)
*EFR*S3*	0.719***	0.827	-0.288	-0.303	-0.141	-0.760
	(3.711)	(1.215)	(-0.318)	(-0.258)	(-0.094)	(-0.516)
*EFR*S4*	0.463***	-0.475	-1.131**	-1.520**	-1.154	-1.583**
	(3.265)	(-1.174)	(-2.052)	(-2.465)	(-1.521)	(-2.120)
*CFFR*S1*	0.065	0.018	-0.456	-0.612	-0.795	-0.869
	(0.516)	(0.046)	(-0.963)	(-1.177)	(-1.199)	(-1.307)
CFFR*S2	**0.178***	0.495*	0.443	-0.199	-0.019	-0.224
	(1.854)	(1.803)	(1.093)	(-0.430)	(-0.035)	(-0.431)
*CFFR*S3*	-0.139	-0.058	0.404	0.697	0.199	0.265
	(-1.076)	(-0.174)	(0.730)	(1.041)	(0.262)	(0.361)
*CFFR*S4*	0.028	0.356	-0.423	-0.118	-0.424	-0.471
	(0.297)	(1.237)	(-1.156)	(-0.282)	(-0.912)	(-1.010)
Adjusted R2	0.061	0.032	0.099	0.088	0.081	0.081

Variable definitions:
Subgroup S3: Negative EFR with positive CFR (i.e., OPDFR with bad news in earnings)
Subgroup S4: Negative EFR with negative CFR (i.e., SAMEFR with bad news in earnings)

TABLE 9
Analyst Full-text Report Rationales for Opposite Direction Cash Flow Forecast Revisions (CFFR) and Earnings Forecast Revisions (EFR)

Rationale of for Issuing OPDFR	News in Forecast Revisions			
	Positive EFR with negative CFFR		Negative EFR with positive CFFR	
	No. of Appear-ances	%	No. of Appear-ances	%
A. Rationale that requires access to management				
Changes in Deferred Taxes and Other Tax Related	5	45%	10	38%
Changes in Inventories, Receivables, Cash Collection, and Days Sales Outstanding (DSO)	1	9%	7	27%
Changes in Other Transitory Reasons (including Asset Impairment)	2	18%	5	19%
Changes in Depreciation, Depletion, and Amortization (DD&A), excluding Asset Impairment	1	9%	4	15%
Changes in Selling, General and Administrative Expenses (SG&A)	1	9%	3	12%
Changes in Overall Cost Structures	3	27%	2	8%
Sub-total – Access to management	13		31	
B. Rationale that can be inferred with publicly available information				
Changes in Commodity Prices	2	18%	3	12%
Changes in Expected Interest Expenses	0	0%	3	12%
Sub-total – Publicly available	2		6	
No. of Documented Rationales	**15**		**37**	
No. of Reports with Documented Rationale(s)	11		26	